

# Distributed Intelligence in Wireless Networks

XIAOLAN LIU<sup>1</sup> (Member, IEEE), JIADONG YU<sup>2</sup> (Member, IEEE),  
YUANWEI LIU<sup>3</sup> (Senior Member, IEEE), YUE GAO<sup>4</sup> (Senior Member, IEEE),  
TOKTAM MAHMOODI<sup>5</sup> (Senior Member, IEEE),  
SANGARAPILLAI LAMBOTHARAN<sup>1</sup> (Senior Member, IEEE),  
AND DANNY HIN-KWOK TSANG<sup>2,6</sup> (Life Fellow, IEEE)

<sup>1</sup>Institute for Digital Technologies, Loughborough University London, E20 3BS London, U.K.

<sup>2</sup>Internet of Things Thrust, The Hong Kong University of Science and Technology (Guangzhou), Guangzhou 511400, Guangdong, China

<sup>3</sup>School of Electronic Engineering and Computer Science, Queen Mary University of London, E1 4NS London, U.K.

<sup>4</sup>School of Computer Science, Fudan University, Shanghai 200438, China

<sup>5</sup>Department of Engineering, King's College London, WC2R 2LS London, U.K.

<sup>6</sup>Department of Electronic and Computer Engineering, The Hong Kong University of Science and Technology, Hong Kong, SAR, China

CORRESPONDING AUTHOR: J. Yu (e-mail: jiadongyu@ust.hk)

This work was supported in part by the Engineering and Physical Sciences Research Council (EPSRC) under Grant EP/R006385/1, Grant EP/X012301/1, and Grant EP/R00711X/2; in part by the Guangzhou Municipal Science and Technology Project under Grant 2023A03J0011; in part by the Guangdong Provincial Key Laboratory of Integrated Communications, Sensing and Computation for Ubiquitous Internet of Things; in part by the U.K. Government Funded Project under the Future Open Networks Research Challenge sponsored by the Department of Science Innovation and Technology; and in part by the Royal Society under Grant IEC01112.

**ABSTRACT** The cloud-based solutions are becoming inefficient due to considerably large time delays, high power consumption, and security and privacy concerns caused by billions of connected wireless devices and typically zillions of bytes of data they produce at the network edge. A blend of edge computing and Artificial Intelligence (AI) techniques could optimally shift the resourceful computation servers closer to the network edge, which provides the support for advanced AI applications (e.g., video/audio surveillance and personal recommendation system) by enabling intelligent decision making on computing at the point of data generation as and when it is needed, and distributed Machine Learning (ML) with its potential to avoid the transmission of the large dataset and possible compromise of privacy that may exist in cloud-based centralized learning. Besides, the deployment of AI techniques to redesign end-to-end communication is attracting attention to improve communication performance. Therefore, the interaction of AI and wireless communications generates a new concept, named native AI wireless networks. In this paper, we conduct a comprehensive overview of recent advances in distributed intelligence in wireless networks under the umbrella of native AI wireless networks, with a focus on the design of distributed learning architectures for heterogeneous networks, on AI-enabled edge computing, on the communication-efficient technologies to support distributed learning, and on the AI-empowered end-to-end communications. We highlight the advantages of hybrid distributed learning architectures compared to state-of-the-art distributed learning techniques. We summarize the challenges of existing research contributions in distributed intelligence in wireless networks and identify potential future opportunities.

**INDEX TERMS** Distributed intelligence, distributed machine learning, edge computing, end-to-end communications, federated learning, split learning.

## I. INTRODUCTION

### A. NATIVE-AI WIRELESS NETWORKS

**I**N THE upcoming wireless networks, apart from developing new spectrum technologies and the support of

simultaneous communications and sensing as well as extreme connectivity requirements and other use cases, it is expected that machine learning (ML) and artificial intelligence (AI) will play a defining role in the development of end-to-end

networks across the design, deployment, and operational phases [1]. Recently, AI techniques have been successfully deployed in the subjects, including computer vision, natural language processing (NLP), and smart decision-making. In wireless communications, the introduction of AI techniques makes researchers rethink and revisit classical approaches that were developed and implemented based on the scientific breakthroughs by Shannon and Wiener, so as to discover new theories and achieve advanced technological breakthroughs for the upcoming 6G wireless networks. Due to its easy implementation in terms of model training and inference, AI techniques are widely used to provide advanced intelligent applications at the network edge, which then brings new challenges for improving network performance. The reinforcement learning (RL) techniques, as an important branch of the AI algorithm family, provide a new paradigm for solving resource allocation and network management problems without the need of finding analytic solutions and formulating dynamic programming, which can obtain solutions for each step dynamically in real-time. Moreover, the implementation of AI techniques makes it possible to combine source and channel coding as well as communication of data with the intended use by an application, and embrace the hardware constraints and undesired effects of the communications channel rather than fighting them. Therefore, with the advancement in wireless networks and their software-defined capabilities, AI will become native and ubiquitous in wireless networks as the role of problem solver and service requester [2]. The definition of native AI wireless networks provides a new vision of traditional wireless networks by deeply integrating AI techniques into every aspect of the wireless networks, such as communications technologies, information technologies, and data technologies. It involves the intersection of AI techniques and wireless networks from the aforementioned three aspects. Native AI wireless networks redefine the device-pipe-cloud, bring the support for distributed AI services, and truly enables pervasive intelligence over every point in the communication system. In this article, we summarize the current research towards achieving the native AI wireless networks from the following three aspects [2], [3], AI-based network optimization and management, AI-empowered wireless communication and AI-enabled distributed data processing.

### B. AI-ENABLED DISTRIBUTED DATA PROCESSING

Currently, there are hundreds of billions of wireless devices (e.g., 13.8 billions Internet of Things (IoT) devices [4], 6.37 billions smartphones [5] and 5 millions drones [6] etc.) around the world, and the number is expected to increase faster in the next decade. The massive devices are equipped with increasingly advanced sensors, computing, and communication capabilities, and they are geographically distributed in the different smart-x environments, e.g., smart homes, smart cities, and smart agriculture, with the capability to undertake various crowd-sensing tasks [7], to extract features from a large amount of data and make decisions

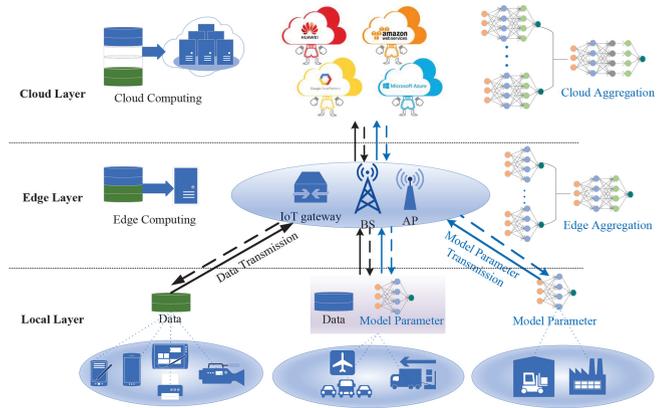


FIGURE 1. The illustration of distributed intelligence in wireless networks.

using Machine Learning (ML) algorithms, especially Deep Learning (DL) (e.g., Convolutional Neural Network (CNN) and deep neural network (DNN)). In the upcoming 6G communications, each network element will natively integrate communication, computing, and sensing capabilities, facilitating the evolution from centralized intelligence in the cloud to ubiquitous intelligence on deep edges. As shown in Fig. 1, 6G will employ a deep-edge architecture to enable massive machine learning in a distributed and collaborative manner. This three-layer architecture integrates the cloud platform (e.g., cloud servers), the edge devices (e.g., WiFi router, Base Stations (BSs), IoT gateway or micro-datacenter), local devices (e.g., smartphones, IoT devices, and vehicles), and advanced wireless communications, which can support AI-enabled applications at the edge of wireless networks [8]. The use of the edge layer pushes the computational resources geographically closer to the local devices compared to the cloud platform, and thus the physical proximity between the computational servers and information-generation sources promises the advantages of edge computing, including low latency, high energy efficiency, proper privacy protection, and reduced bandwidth consumption.

From Fig. 1, to support AI services at the edge, the ML models can be learned by either centralized or distributed ML model training. For conventional centralized learning, the massive data generated at the local layer can be directly transmitted to the edge layer or cloud layer for learning ML models. Recently, an emerging distributed ML architecture built on deep-edge intelligence has been shown to have the potential to meet the large-scale intelligence requirements of future society and manufacturing. This means the ML models can be learned through the collaboration of distributed devices and a centralized parameter server. From Fig. 1, the model aggregation can be performed at the edge layer by deploying the parameter server at BS, WiFi router, or IoT gateway. Also, a hierarchical distributed learning architecture can be applied by performing model aggregation at the cloud layer for complex ML model training and inference. For simplicity, we will consider the BS as the parameter

server located at the edge layer to illustrate the architecture of edge computing and distributed learning in wireless networks.

The conventional centralized learning approach of offloading raw data to the edge incurs a huge cost (e.g., large time delay, energy consumption, and wide bandwidth) due to the transmission of a large datasets, and reveals privacy and security concerns. To address these challenges, distributed learning was proposed to let users keep their private data locally and share only model parameters or smashed data instead of raw data to a central server [9]. Federated Learning (FL) as a popular distributed learning technique was first proposed to provide communication-efficient distributed ML model training, in which the users perform local model training on their own private datasets, and then share their local model updates instead of raw data to a central server where a model parameter aggregation is performed to update the global model [10]. Considering the diversity of users with different computational capabilities and resources (e.g., the size of local datasets, different data distributions, and wireless channel qualities), FL is not always efficient since it requires that all the users are capable of computing gradients but this may not be possible for some users. Moreover, the users have to offload the local updates of the full ML model and this causes large communication overhead for users when the ML model is complex. Fortunately, users with weak computational capability can choose centralized learning by migrating the training task to the server or a distributed learning approach that only runs a partial ML model locally with the rest running at the server, and it is known as Split Learning (SL). To this end, a hybrid learning architecture could be more energy-efficient for heterogeneous wireless networks to benefit from different learning approaches, such as Hybrid Centralized and Federated Learning (HCFL) [11], and Hybrid Split and Federated Learning (HSFL) [12], [13]. Moreover, in distributed learning, the contributions of different users to the global model update are different, and thus scheduling the users with more contributions, i.e., large local model updates and good channel qualities, for participating in model training is important. Since participation consumes users' energy and could possibly reveal their privacy, not all users are actively willing to contribute to global model training without sufficient compensation. The incentive mechanism was studied to encourage users to join the model training by introducing rewards and payment for them based on Shapley value, Stackelberg game, auction, and contract theory [14]. On the other hand, due to the diversity of users, each user may not complete their local computation at the same time. Those users completing local model updates slower than others are called stragglers. When performing model aggregation, the stragglers will cause an adverse effect to the convergence of the global model [15]. Therefore, asynchronous distributed learning was introduced to address the harmful effects of the stragglers by adopting dynamic learning rates and using a regularized loss function [16].

### C. AI-BASED NETWORK OPTIMIZATION AND MANAGEMENT

Recently, a wide range of new applications, like mobile payment, mobile games, and eXtended Reality (XR) services (including Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR)), have been deployed in wireless networks. This requires intelligent use of communications, computing, control, and storage resources from the network edge to the core, and across multiple radio technologies and network platforms. Therefore, to meet diverse service requirements, the existing technologies, such as Software Defined Networks (SDN), Network Functions Virtualization (NFV), and network slicing will need to be further improved relying on AI-based methods. Last but not least, the volume and variety of data generated in wireless networks are growing significantly. This requires data-driven algorithms, such as ML algorithms, to extract insights from the massive data and it opens up great opportunities for intelligent network planning to achieve real-time additivity to dynamic network environments. Therefore, AI will be an indispensable tool to facilitate intelligent learning, reasoning, and decision making in 6G wireless networks.

AI techniques are powerful for the quick analysis of big data and extracting insights from the data, which has achieved sustained success in many research areas, including automatic control in robotics, image processing in computer vision, speech recognition, and natural language processing. In Fig. 1, the introduction of the edge layer provides distributed computing resources for the implementation of AI techniques in analyzing the big data generated at the local layer. Benefiting from distributed learning architecture, complex AI models can be trained and inferred efficiently at the network edge. The big data analytics accomplished by AI techniques, including four different types, namely descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics, can support both AI services deployed at the network edge and network performance improvement in wireless networks.

Due to the increase in network scale, density, and heterogeneity, it is hard or even impossible to model such a dynamic wireless system with traditional optimization approaches. The conventional network optimization assumes the objective function to be available in nice algebraic forms and allows an optimizer to evaluate a solution by simple calculation [2]. However, the mapping between a decision and its effect on the physical system is cost prohibitive to define and may not be analytically available. Recent advances in AI technologies, such as statistical learning, RL, and DL algorithms, can solve the formulated complicated network optimization problems in future wireless networks since they can find the asymptotically optimal solutions iteratively using the Stochastic Gradient Descent (SGD) methods. Specifically, the RL techniques including Deep RL (DRL), Multi-Armed Bandit (MAB) theory, and multi-agent RL algorithms can establish a feedback loop between the

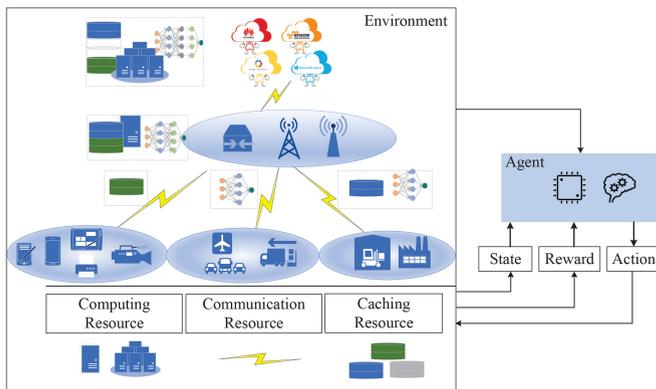


FIGURE 2. AI techniques provide intelligent solutions for wireless communications.

decision-maker and the physical system, so that the decision-maker can iteratively refine its action based on the system's feedback to reach the optimality eventually. As shown in Fig. 2, RL techniques have been broadly applied to address several emerging issues in communication and networking, including resource allocation, wireless caching, computation offloading, and user scheduling, etc.

#### D. AI-EMPOWERED WIRELESS COMMUNICATIONS

As discussed above, to support AI services in wireless networks, the data generated by the end users need to be offloaded to the central server that uses centralized learning algorithms to unlock their potential, or kept locally by relying on distributed learning and offloading local model parameters. In both scenarios, the requirements on communication channel quality are high since offloading raw data needs large bandwidth and high data rate communication while offloading model parameters need ultra-reliable and low latency communication links. The current 4G/5G is restricted to support AI services with high requirements on Key Performance Indicators (KPI), and thus ML techniques have been studied in wireless communications to improve those KPI metrics [17]. The potentials of ML techniques have been widely studied in block-based communication systems to support different locally optimized objectives, such as signal compression, modulation, channel coding, and so on. To realize global optimization in communication systems, ML for end-to-end systems has been proposed to further enhance communication efficiency [18].

With the development of wireless communications that involve emerging advanced technologies, the complicated environment brings unprecedented challenges to communication system modeling. In conventional chain-shape block-based communication systems, DL has been deployed in different independent modules for multiple purposes with significantly improved performance, such as interference alignment [19], jamming resistance, modulation classification [20], physical coding [21] and so on. However, existing approaches with separate blocks can not holistically capture the comprehensive aspects of the real-world system.

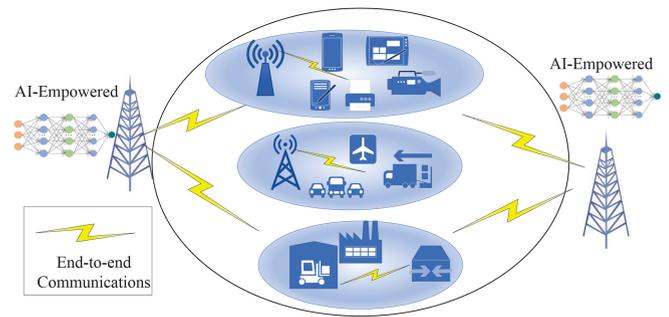


FIGURE 3. AI-empowered end-to-end communications.

Therefore, the potential of AI-empowered end-to-end communication systems to support future networks has been discussed [2]. As shown in Fig. 3, the envisioned intelligent end-to-end system can realize self-optimization communication with the help of advanced sensing, data collection, and AI technologies.

#### E. MOTIVATION AND CONTRIBUTIONS

The aforementioned research works have laid the basic foundation for understanding the development of applying AI techniques in wireless communications. There are some existing surveys and tutorials that have tried to address this interdisciplinary problem of AI and wireless communications from the aspects of edge intelligence [31], [32], and distributed ML in wireless communications [9], [22], [23], [24], [25], [26], [27], [28], [29], [30], but their focus is different from our work. Particularly, The authors in [31] focused on an overview of the deep learning applications at the network edge. In [32], the authors mainly identified edge intelligence from edge caching, edge training, edge inference, and edge offloading. In [9], [22], [23], [24], the authors mainly reviewed the fundamental concepts and techniques of distributed ML, with a focus on FL algorithms. In [25], the authors presented several applications using FL algorithms in mobile edge networks and further introduced the implementation challenges of FL algorithms. Similar works have been discussed in [26], [27], the authors illustrated the basic principles behind implementing FL in supporting efficient and intelligent wireless communications. Apart from FL, the authors in [28], [29], [30] explored a broad aspect of distributed ML in wireless communications. Specifically, the latest applications of distributed ML in wireless networks and the practical challenges of which, as well as privacy and security concerns were reviewed in [28]. In [29], the authors presented the communication-efficient techniques and DML frameworks based on a few selected use cases. Furthermore, the use of communication techniques for the efficient deployment of distributed learning algorithms in wireless networks have been provided in [30], in which an overview of several emerging distributed learning paradigms, including FL, distributed inference, and federated distillation was presented.

TABLE 1. Comparison between related existing survey.

Year of publication		2021	2021	2021	2021	2020	2020	2021	2021	2021	2021	
Existing survey		[22]	[23]	[9]	[24]	[25]	[26]	[27]	[28]	[29]	[30]	Our work
Main topic		FL/DML				FL/DML for wireless communications						Distributed intelligence in wireless networks
Main ML techniques	DL	✓	✓	✓		✓	✓				✓	✓
	RL			✓							✓	✓
	MARL										✓	✓
Distributed learning	FL	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Beyond FL						✓		✓	✓	✓	✓
ML for communications	Block-based system						✓					✓
	End-to-end system											✓
Communications for distributed learning	Aggregation	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓
	Compression	✓	✓			✓	✓	✓		✓	✓	✓
	Security and privacy		✓	✓	✓	✓	✓	✓	✓			✓
	Asynchronous			✓			✓					✓
	User scheduling									✓		✓
Others	Edge computing	✓	✓			✓		✓			✓	✓
	Incentive mechanism					✓	✓					✓
	Architectures	✓	✓							✓		✓

Although the aforementioned research contributions present either edge intelligence or distributed ML in wireless networks, the analysis of different ML techniques for edge computing, the implementation of distributed learning architectures in wireless networks, and the use of DL techniques for improving end-to-end communication have not been covered. Besides, a clear illustration of the development of AI algorithms in wireless communications from different aspects is missing. Motivated by the aforementioned inspirations, we develop this survey paper with the goal of comprehensively investigating the major issues, challenges, and opportunities of distributed intelligence in wireless networks that falls under the umbrella of native AI wireless networks, with a focus on intelligent data processing, network management optimization, and communication performance improvement. Table 1 illustrates the comparisons of this survey with the existing relevant surveys and tutorials.

To highlight the significance of our contributions, this survey starts with the introduction of native AI wireless networks, which provides the readers with clear concepts of the interaction of ML techniques and wireless communications from AI-assisted wireless networks and wireless communication supporting AI services at the network edge. We continue to present AI-enabled distributed data processing with a focus on two aspects, the implementation of distributed learning architectures in wireless networks, and ML techniques assisted edge computing, especially using RL techniques for computation offloading at the network edge. Next, communication-efficient technologies for distributed learning are introduced. We then address the use of DL techniques to improve wireless communication performance. Finally, we identify the existing challenges and potential opportunities for achieving distributed intelligence in

wireless networks. The main contributions of this survey are stated as follows:

- 1) We present a comprehensive survey on recent advances and state-of-art in deploying distributed intelligence in wireless networks. The basic concepts of edge computing and distributed learning techniques are introduced and key advantages are summarized. Moreover, the research challenges and potential opportunities are also discussed.
- 2) We review the state-of-art hybrid learning architectures and asynchronous distributed learning for heterogeneous networks. We also demonstrate that the HSFL framework achieves better learning performance in wireless networks with diverse users. Moreover, we investigate the motivation of wireless users for joining in global model updates by reviewing the design of incentive mechanism schemes.
- 3) We investigate different ML techniques for optimizing computation offloading and resource management in edge computing networks. RL techniques, including DRL, multi-agent RL, federated RL (FRL), and other learning techniques, such as DL and imitation learning, are reviewed. Furthermore, we summarize the application scenarios and complexity of those ML techniques and traditional optimization methods. The challenges of exploiting the existing ML techniques for complicated edge computing have been identified and the potential solutions are also underlined.
- 4) We identify the challenges of traditional communication technologies, followed by the review of the state-of-art communication-efficient technologies, user scheduling and resource management, over-the-air computation, and gradient compression.



FIGURE 4. The structure of this survey.

- 5) We identify the potentials of DL in wireless communications with a review of investigating DL techniques to optimize the traditional communication blocks and redesign end-to-end communication structures. Moreover, DL for current advanced communication technologies is also reviewed.
- 6) We provide future opportunities and challenges to improve network efficiency, cope with diverse users, and prevent privacy leakage and security concerns for distributed intelligence in wireless networks.

## F. ORGANIZATION

The rest of this paper is organized as follows. Section II provides the fundamentals of edge computing, ML algorithms, and distributed learning techniques. Section III discusses different AI techniques that enabled edge computing. In Section IV, distributed learning in wireless networks is

discussed. Followed by the communication-efficient technologies for distributed learning are illustrated in Section V. Section VI reviews investigating DL techniques to optimize the traditional communication blocks and end-to-end communications. The open issues and future opportunities are discussed in Section VII. The structure of this survey paper is depicted in Fig. 4.

## II. THE FUNDAMENTALS OF DISTRIBUTED INTELLIGENCE OVER WIRELESS NETWORKS

### A. EDGE COMPUTING

Edge/fog computing was proposed to pave the way for the evolution of new era applications and services, which follow a wireless distributed computing framework and are promising to handle data processing for the explosive growth of data generated from massive wireless devices (e.g., mobile phones, sensors, drones, etc.). It is processing the massive amount of data generated from geographically distributed

users by pushing the computational resources from the central to the network edge which is near the data source. Recently, increasingly advanced applications, such as mobile payment, smart healthcare, mobile games, and XR applications [33], put higher requirements on the resource capacity of smart devices. Instead of replacing cloud computing that was first put forward by Google [34], edge computing is introduced as a complementary paradigm to address the challenges of limited bandwidth, large latency, and high energy consumption existing in cloud computing by letting the computational resources be accessible ubiquitously through deploying a large number of edge nodes in a distributed manner at the network edge. As shown in Fig. 1, an edge layer is added to the conventional cloud-local wireless networks, and more distributed computational resources are deployed at the edge layer to provide edge computing.

The first edge computing concept cloudlet [35] was proposed to bring the computational or storage resource closer to the users. Cloudlet is a small-scale data center or a cluster of computers designed to quickly provide cloud computing services to mobile devices, such as smartphones, tablets, and wearable devices, within close geographical proximity. To support the big data processing for advanced applications with billions of connected devices at the network edge, a more general concept of edge computing, fog computing with a focus on IoT applications, was introduced by Cisco as it can offer: a) low latency and location awareness due to proximity of the computational devices to the edge of the network, b) wide-spread geographical distribution when compared to cloud computing, c) interconnection of a large number of end devices (e.g., wireless sensors), and d) support of streaming and real-time applications. However, the aforementioned edge computing concepts are not integrated into the architecture of the mobile network, which causes the Quality of Service (QoS) and Quality of Experience (QoE) for mobile users can be hardly guaranteed. Therefore, MEC network was proposed to place computation capabilities and service environments at the edge of cellular networks [36]. By deploying edge servers at the cellular BSs, mobile users can support advanced applications and services flexibly and quickly. The European Telecommunications Standards Institute (ETSI) Industry Specification Group (ISG) further extends its name of MEC to Multi-access Edge Computing (MEC) to embrace the challenges of more wireless communication technologies, such as Wi-Fi [37].

With the distributed architecture, we can summarize the importance and benefits of edge computing as follows [38].

- *Providing real-time QoS*: The IoT devices and wearable devices are designed for delay-sensitive use cases, and most of them demand high QoS requirements due to the mobile and interactive environment. For instance, the healthcare data generated by the body-worn sensors need to be processed immediately in case of an emergency [39]. As another example, the AR and VR experiences rely on the graphics rendering on the edge/cloud to augment latency-sensitive on-device head

tracking, controller tracking, hand tracking, and motion tracking [40]. The legacy cloud servers cannot support these applications because of the large delay of accessing them through the Wireless Area Network (WAN). Edge computing could provide the solution by deploying the edge servers closer to the users, which reduces the overall latency through high Local Area Network (LAN) bandwidth and decreased number of hops.

- *Decreasing energy consumption*: The limited battery capacity is still a challenge for mobile phones and especially for most IoT devices, and thus reducing energy consumption is always an important goal in wireless networks. Computation offloading has been demonstrated to be an effective method to reduce the total energy consumption by offloading the intensive computational tasks to edge or cloud [41], [42]. It is also stated that offloading tasks to the edge servers result in lower energy consumption compared to offloading them to the cloud platforms. Certainly, executing tasks locally at the device causes the highest energy consumption.
- *Reducing network congestion*: The limited bandwidth of the core network makes it vulnerable to network congestion. In 2020, tens of millions of devices are generating 2.5 quintillion bytes of data per day, and this rate is expected to increase [43]. The conventional approach is to transmit the data through the core network to the cloud servers for processing, which causes a heavy burden on the core network. Edge computing prevents this by keeping the traffic at the edge servers and also optimizes the utilization of the limited bandwidth.
- *Scalability*: the number of mobile users is expected to increase to 10.3 billions and the number of IoT devices will reach 30.9 billions by 2025 [44], which creates a significant scalability problem. The conventional cloud cannot provide a scalable environment for the data and applications due to highly possible network congestion caused by the data transmission of tens of millions of end devices. With edge computing, if one edge server becomes congested and fails to satisfy the incoming requests, the corresponding service can be transferred to another edge server nearby and let the computing service be handled there.

As mentioned above, edge computing has a similar working mechanism as cloud computing, but distributes the computational resources closer to the local devices. Instead of offloading intensive computational tasks to the remote cloud, the end devices recur to the edge servers in the vicinity for computational resources; generally, there are several nearby edge servers that can be accessed by each end device. However, the edge servers have limited power and computational resources compared to the cloud server which is assumed to be super powerful, which makes the computation offloading problem more complicated due to the need of considering edge server selection and resource management [7]. In cloud computing, the key point of computation offloading is to decide whether to offload or not, how much

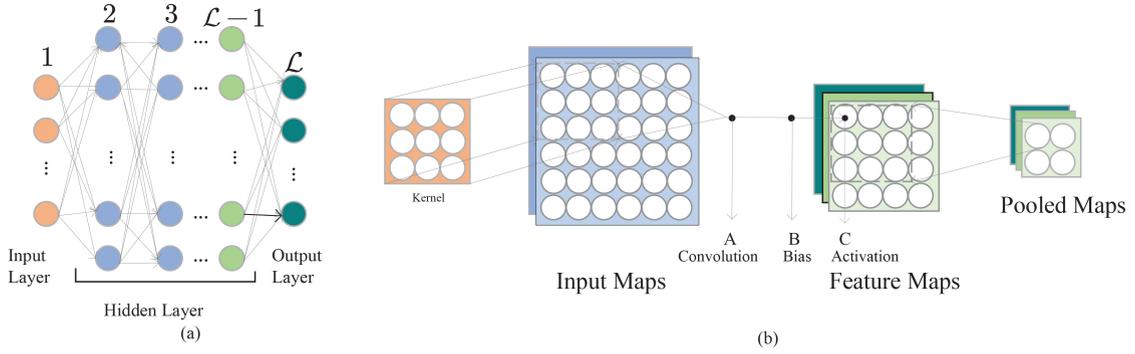


FIGURE 5. The structure of different DL algorithms, (a) DNN, (b) CNN.

and what should be offloaded. In edge computing, in addition to those points, we need to address where and how to offload, and how much resources should be allocated. Recently, researchers have studied the joint computation offloading and resource management problem with the goal of minimizing energy consumption and execution delay [45], [46]. They formulated the joint problem as a combinatorial optimization problem with non-linear constraints and proposed the computation offloading algorithms based on convex optimization [47], [48], Lyapunov optimization [49], [50] and game theory [51], [52]. Moreover, the design of the computation offloading scheme can be modeled as the process of making decisions on offloading and resource allocation by interacting with the dynamic environment, which is then investigated by exploiting the RL algorithms in many research works [53], [54].

## B. THE ML TECHNIQUES

### 1) THE DL ALGORITHMS

The basic data-driven deep learning-based algorithm adopts a fully connected feed-forward neural network with multiple hidden layers to extract the data representation [55]. This multi-layer neural network can be established by supervised learning, unsupervised learning, and RL. Without the knowledge of the mathematical model, deep learning can learn from a large amount of labeled data and the hyper-parameters can be tuned based on the domain knowledge for superior insight extraction. Hence, deep learning has been widely applied to the fields the mathematical description cannot be easily obtained. There are mainly three different kinds of deep learning architectures: DNN, CNN, and Recurrent Neural Networks (RNN) [56]. We will briefly introduce DNN and CNN below.

1) DNN: Generally, DNN is a deeper version of Artificial Neural Networks (ANNs) with multiple layers (more than three hidden layers). The structure of the DNN is shown in Fig. 5 (a) [56]. In DNN, each layer consists of multiple neurons, each of which has an output that is a non-linear function, like the Sigmoid function or ReLU function. To express the DNN propagation principle, we use  $\mathbf{i}_l$  to represent the input of the  $l^{\text{th}}$  layer neurons.  $o_{l,n_e}$  represents the output

of the  $n_e^{\text{th}}$  neuron at  $l^{\text{th}}$  layer.  $\mathbf{W}_l^{(\text{DNN})}$  and  $\mathbf{b}_l^{(\text{DNN})}$  denote the weight matrix and the bias vector of the  $l^{\text{th}}$  layer. Hence, each neuron's output can be expressed as

$$o_{l,n_e} = f_{l,n_e} \left( b_{l,n_e}^{(\text{DNN})} + \mathbf{W}_{l,n_e}^{(\text{DNN})T} \mathbf{i}_l \right), \quad (1)$$

with  $f_{l,n_e}$  as the activation function for the  $n_e^{\text{th}}$  neuron at the  $l^{\text{th}}$  layer, and  $(\cdot)^T$  denotes the transpose.

During the training phase of constructing DNN, the parameter set  $\boldsymbol{\theta}_l = (\mathbf{W}_l^{(\text{DNN})}, \mathbf{b}_l^{(\text{DNN})})$  represents the weights and biases of the DNN model at the  $l^{\text{th}}$  layer, which can be obtained through backpropagation gradient to recursively minimize the loss function until convergence. Conventionally, the gradient descent method is to find the local minimum by taking steps proportional to the gradient of the function, this can be represented by

$$\boldsymbol{\theta}^{(\tau+1)} = \boldsymbol{\theta}^{(\tau)} - \eta \nabla \text{Loss}(\boldsymbol{\theta}^{(\tau)}), \quad (2)$$

where  $\boldsymbol{\theta}^{(\tau)}$  represents the model parameter set at time slot  $\tau$ , and  $\text{Loss}(\boldsymbol{\theta})$  is the loss function with current parameter set,  $\eta$  is the learning rate.

Different from gradient descent which calculates the gradient by taking the whole dataset into account, SGD has been proposed to handle much larger datasets in practical scenarios by calculating the model updates based on the mini-batch of data. This can be formulated as

$$\begin{aligned} \text{Loss}(\boldsymbol{\theta}) &= \sum_{d=1}^D \text{Loss}_d(\boldsymbol{\theta}), \\ \boldsymbol{\theta}^{(\tau+1)} &= \boldsymbol{\theta}^{(\tau)} - \eta \nabla \text{Loss}_d(\boldsymbol{\theta}^{(\tau)}) \end{aligned} \quad (3)$$

where  $D$  is the number of mini-batches of the whole dataset. It has been proved that SGD has a higher probability of avoiding local minimum and data redundancy [57].

2) CNN: Compared to DNN, CNN puts additional convolutional and pooling layers before feeding the data into the neural network [58]. It has been widely utilized to deal with computer vision and signal compression problems. In Fig. 5 (b), the structure of CNN with a two-dimensional (2-D) kernel is plotted. There are three main volumes: input maps, feature maps, and pooled maps. The convolution

TABLE 2. The differences between two DRL approaches.

DRL algorithms	Policy	Characteristics	Training time
Value-based DRL	Only learn deterministic policies	Learn a Value function, struggle with a large number of actions and continuous actions	Less efficient
Policy gradient-based DRL	Can learn deterministic and stochastic policies	Learn a probability distribution of actions, can handle continuous actions	More efficient, find the policy directly

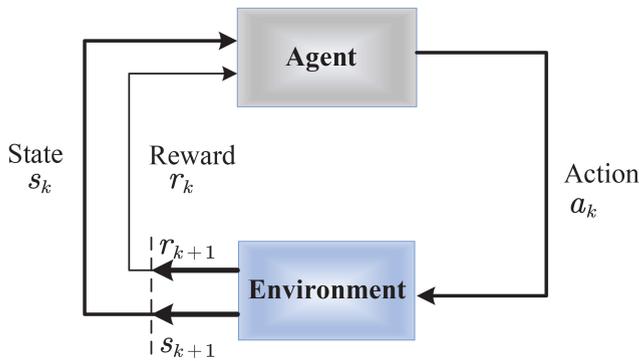


FIGURE 6. The framework of the RL technique.

between a 2-D kernel  $w_{m,n,k}^{CNN}$  and the  $k^{th}$  map at  $(x, y)$  spatial location is the sum of products of the weights of the kernel and the elements of the map that are spatially coincident with the kernel [59]. Specifically,  $m$  and  $n$  are variables that indicate the kernel height and width, respectively. At point  $A$  in Fig. 5 (b), the summation of the overall  $K$  depth of the input volume at spatial coordinate  $(x, y)$  can be written as

$$conv_{x,y} = \sum_k \sum_{m,n} w_{m,n,k}^{CNN} v_{m,n,k}, \quad (4)$$

where  $v_{m,n,k}$  is the value of the spatially corresponding elements on the input maps. Then a scalar bias  $b_{x,y}^{(CNN)}$  is added at point  $B$  in Fig. 5 (b) as

$$z_{x,y} = conv_{x,y} + b_{x,y}^{(CNN)}. \quad (5)$$

Therefore, the feature map can be expressed as

$$a_{x,y} = f(z_{x,y}), \quad (6)$$

with  $f(\cdot)$  as the activation function. Based on the aforementioned steps, the complete feature map can be generated. Next, in the pooling layer, the neurons in the feature maps are then grouped together for average pooling or maximum pooling. During the training stage, the weights of the 2D kernel and the bias of each feature map are learned by minimizing the output error and then performing backpropagation.

## 2) RL TECHNIQUES

As illustrated in Fig. 6, the goal of RL techniques is to create an intelligent agent in the environment that can learn efficient policies to maximize the long-term rewards by taking controllable actions, where the process of the agent taking actions and changing state through interacting with the environment can be modeled as a Markov Decision Process

(MDP). The DRL approach is a combination of deep learning and RL techniques, but it focuses more on RL and aims to solve decision-making problems. The role of deep learning is used to explore the powerful representation ability of DNN to represent a large number of states and approximate the action values to estimate the quality of the action in the given states, so that the DRL is able to solve the explosion of state-action space or continuous state-action space problems. The typical application scenario of DRL is to solve various scheduling problems, such as decision-making problems in games, rate selection of video transmission, and resource allocation in wireless communications. There are two main DRL approaches introduced as follows, and the differences between these two are summarized in Table 2.

1) Value-based DRL: As a representative of value-based DRL, Deep Q-Network (DQN) was proposed to approximate action values using DNN, which breaks the curse of high-dimensional input data and successfully maps it to actions [60]. However, the non-linear approximator, DNN, makes DQN unstable due to the correlations that exist in the sequence of observations. Hence, the experience replay is used to remove the correlations by using a random sample of prior actions instead of the most recent action to proceed. Besides, the Double-DQN algorithm that can reduce the observed overestimated action values was studied in [61], and the Dueling-DQN proposed in [62] can learn which states are (or are not) valuable without having to learn the effect of each action at each state.

2) Policy Gradient-based DRL: Policy gradient is a policy-based RL algorithm, which relies upon optimizing parametrized policies with respect to the long-term cumulative reward by gradient ascent. Policy gradient algorithms typically proceed by sampling the stochastic policy and adjusting the policy parameters in the direction of greater cumulative reward. Instead, the Deterministic Policy Gradient (DPG) algorithm was considered in [63], and it is demonstrated that it has a significant performance advantage over stochastic policy gradients. By combining DQN and DPG, the Deep Deterministic Policy Gradient (DDPG) algorithm was proposed by using the DNN to parameterize the policy that is then optimized by the policy gradient method [64]. Besides, there are a few other state-of-art policy-based DRL algorithms, such as Asynchronous Advantage Actor-Critic (A3C) that enables parallel actor-learners to train the neural network [65], Trust Region Policy Optimization (TRPO) that is effective for optimizing large non-linear policies like neural networks [66], and Proximate Policy Optimization (PPO) that improves TRPO with simpler

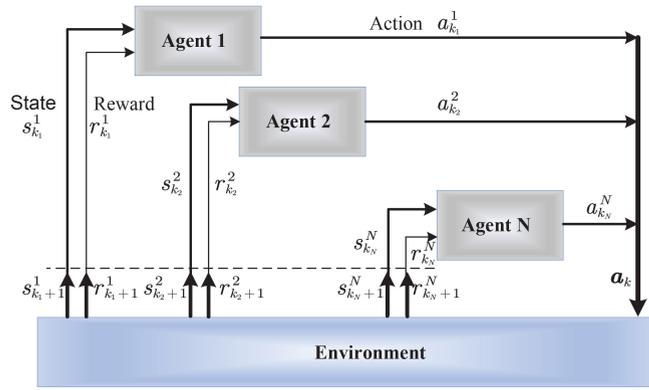


FIGURE 7. The framework of multi-agent RL framework.

implementation [67]. Specially, all of them rely on an *Actor-Critic* (AC) framework, in which both the *Critic* and *Actor* functions are parameterized with DNN, known as critic network and actor-network. The critic network is used to estimate the value function of the state-action pair, while the actor-network is in charge of policy updating in the direction suggested by the critic network.

### 3) MULTI-AGENT RL TECHNIQUES

In the aforementioned RL algorithms, an RL agent is modeled to perform sequential decision-making by interacting with the environment, which is always formulated as an MDP problem. However, most of the successful RL applications, e.g., the games of Go and Poker, robotics, and autonomous driving, involve the participation of more than one single agent, which naturally falls into the realm of multi-agent RL [68]. The research on multi-agent RL can be traced back to the 1990s [69], [70], and most recently it re-emerge due to the advances in single-agent RL techniques. Specifically, multi-agent RL can address the sequential decision-making problem of multiple agents that operate in a common environment, each of which aims to optimize its own long-term return by interacting with the environment and other agents [68].

Markov game, also known as a stochastic game, is a general extension of MDP in the multi-agent scenarios to include multiple adaptive agents with an interacting or competing goal, and the framework of the Markov game has long been used to develop multi-agent RL algorithms originated from [70]. Different from the RL algorithm the environment changes its state only based on the action of one agent, both the evolution of the system and the reward received by each agent depend on the joint action of all agents in the multi-agent RL algorithm as shown in Fig. 7. The multi-agent RL algorithms are categorized into three groups according to the types of multi-agent tasks that they address.

- *Cooperative setting* - a fully cooperative setting is the case that all the agents collaborate to optimize a common long-term return.

- *Competitive setting*- in a fully competitive setting, the return of agents usually sums up to zero, which is typically modeled as a zero-sum Markov game.
- *Mixed setting*- a mixed setting is usually modeled as a general-sum game, where no restriction is imposed on the goal and the relationship among the agents.

### C. THE STATE-OF-ART DISTRIBUTED LEARNING TECHNIQUES

The traditional centralized ML algorithms typically gather the distributed raw data generated at different devices/organizations to a single central server/cluster with shared data storage as shown in Fig. 8 (a). The centralized approach faces the challenges of large computational power and long training time, and most importantly, serious data privacy and security concerns. When the training data becomes huge, e.g., a terabyte of data, or is inherently distributed to be stored and processed on individual machines, the model training process can be carried out by exploiting distributed resources (e.g., computational resources, power, and data) over the end devices, which is distributed ML.

Distributed ML has been investigated since 2000 on deploying the structure of distributed computing to speed up the training process so as to reduce the training time. Multiple parallelization techniques have been introduced into distributed ML, such as MapReduce and Hadoop framework relying on distributed file system [71], Apache Spark saving expensive reads from the disk [72] and Parameter Server with relaxing the stringent requirement of synchronization [73], which could address the large-scale data challenges. More details about the popular architectures of the conventional distributed ML can be found in [74]. In wireless networks, due to the naturally distributed characteristics of the data generated over the wireless devices, a new concept of distributed ML, simply called distributed learning in this article, appears to train a global ML model by keeping the dataset locally at user devices, which exploits the distributed computational resources of the wireless devices, saves the communication cost, and protects the users' privacy. The architecture of distributed learning is shown in Fig. 8 (b). In the following, we will introduce two state-of-the-art distributed learning algorithms, FL and SL algorithms.

#### 1) THE FL TECHNIQUES

FL is a special type of distributed learning, where multiple users collaboratively train a global model while keeping the raw data distributed to local users without being moved to a single server or data center. The architecture of FL is shown in Fig. 9. FL is flexible and reliable to train ML models in a heterogeneous system. This is because of its unique characteristics: a) it does not require direct raw data transmission from the distributed users, b) it exploits the distributed computational resources from multiple regions and organizations, c) it generally takes advantage of encryption or other defense techniques to ensure the data privacy and security.

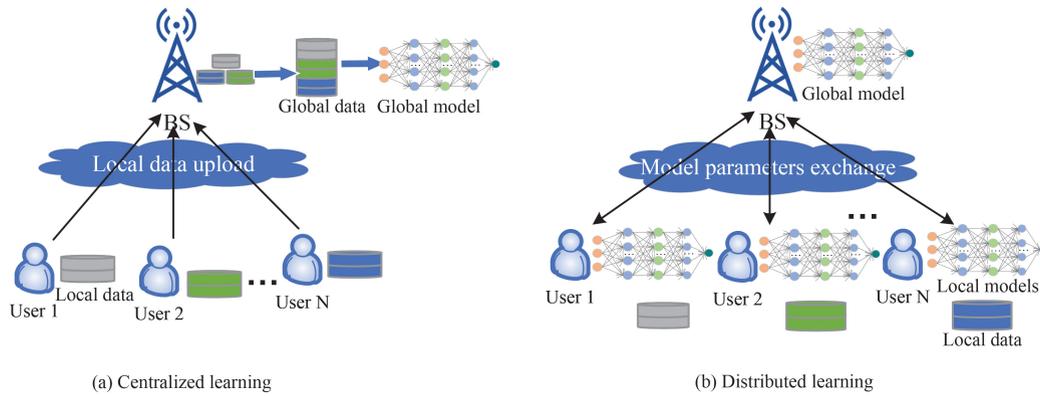


FIGURE 8. The architecture of (a) centralized learning and (b) distributed learning.

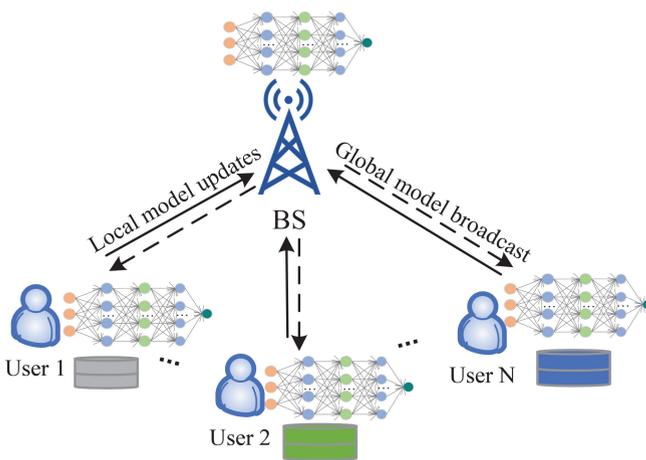


FIGURE 9. The learning procedure of FL technique.

FL was first proposed in [10] to handle the machine learning model training with decentralized data from mobile devices, which was demonstrated to be robust for unbalanced and non-Independent and Identically Distributed (non-IID) data distributions. As a distributed learning scheme, FL brings the learning task to the edge level instead of performing model training at a central entity, which enlightens a series of studies on FL over different areas. For instance, FL has been successfully applied to Google’s predictive keyboards [75]. In FL, the communication overhead of FL is proportional to the number of model parameters and it is significantly reduced especially when the users hold local datasets that are much larger than the model size, which also avoids the transmission of large raw datasets. However, FL struggles with supporting distributed model training for DNNs with large and complex model parameters over capacity-limited wireless channels.

## 2) THE SL TECHNIQUES

SL, also known as split neural network (SplitNN), was proposed to address the problem of training a DNN model over multiple data entities. In SL, a DNN is split into multiple

sub-networks (e.g., each sub-network includes a few NN layers) by the cut layer, each of which is trained on a different entity [76] as shown in Fig. 10 (a). Similar to FL, SL also provides a solution to train a DNN model while keeping the raw data locally at the distributed users, whereas the users only train a sub-network of the DNN model instead of the full model, and the other sub-network is trained by a more powerful parameter server. The architecture of SL is shown in Fig. 10 (b).

Take the sequential SL as an example, all the users collaborate with the parameter server to train a full ML model sequentially. The parameter server distributes a lower sub-network to the users and itself holds the upper sub-network, and then the training of the full model is carried forward on the user’s local dataset by transferring the output of the cut layer to the parameter server. Next, the parameter server calculates the loss values and the gradients, then updates its upper sub-network, and sends the gradients of the cut layer back to the user for updating its lower sub-network. At last, the user returns the updated sub-network to the server, and then the training process of the next user will start. In this case, only the outputs of the cut layer are shared between users and the parameter server, no raw data is shared so that user privacy and security are protected. SL was first proposed to be applied in medical applications [77], [78], where a model is trained with the sensitive health data from different hospitals.

The communication cost of SL mainly depends on two parts: the model size of the first few NN layers prior to the split and the size of the activations that is up to the size of the dataset owned by the user. Therefore, SL requires much lower communication bandwidth when training over the dataset distributed over a large number of users but is relatively larger in settings with a smaller number of users [79].

## D. DISCUSSION AND OUTLOOK

Given the increasing research contribution to the interdisciplinary of AI techniques and wireless communication at the network edge, its advantages are becoming obvious,

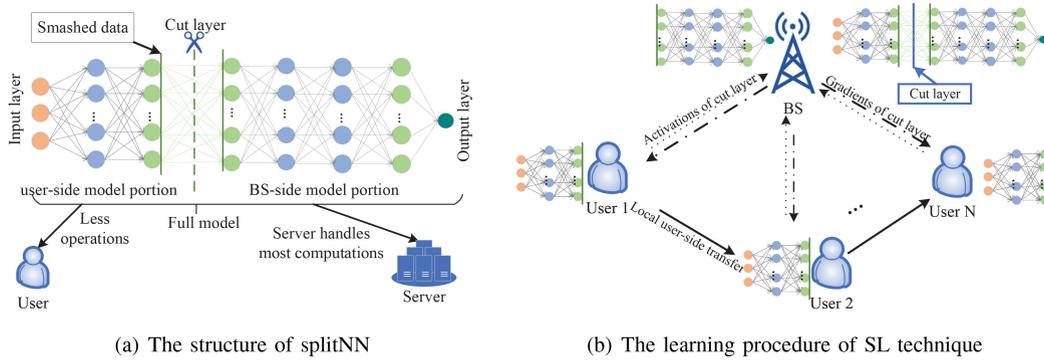


FIGURE 10. The learning mechanisms of SL techniques.

especially in decision-making, network management, and AI services support. ML techniques have become a powerful tool for data analytics and intelligent decision-making, which is able to extract insights from data and hence provide intelligent network solutions and advanced applications at the network edge. This is particularly essential in large-scale wireless networks supporting a large number of distributed BSs and users. At the time of writing the native-AI-enabled wireless networks is still in their infancy. Investigating the proper ML technique for the specific application scenario is challenging. Hence, further research is required to identify the cooperation of different ML techniques in next-generation wireless networks. Moreover, an important issue that needs to be addressed is to improve distributed learning performance, i.e., less convergence latency and higher energy efficiency, under a dynamic environment. Specifically, the design of new distributed learning architectures based on FL and SL needs more attention when considering the heterogeneity of wireless networks.

### III. DISTRIBUTED LEARNING IN WIRELESS NETWORKS

To support a wide range of emerging AI services in wireless networks, the conventional approach is to collect all the raw data from the users and then train the ML models in a centralized fashion as shown in Fig. 1. However, the centralized learning approach is restricted by limited bandwidth, energy consumption, privacy, and security concerns. Therefore, distributed learning, including FL and SL algorithms, has been proposed to allow the parameter server and wireless users to collaboratively train the ML models by only exchanging model parameters instead of raw data as shown in Fig. 1. Benefiting from the distributed learning architecture, a broad range of advanced AI applications can be deployed at the network edge.

#### A. HYBRID DISTRIBUTED LEARNING ARCHITECTURES FOR HETEROGENEOUS WIRELESS NETWORKS

As a representative of distributed learning, FL has been studied a lot recently in wireless networks to improve communication efficiency for training ML models in a distributed manner, which is deployed at the network edge to exploit

the computational capabilities of the end users. The FL architecture requires that all the users are capable of gradient computation, which is hard to be satisfied considering the diversity of the users in terms of computational capacities. Besides, the local dataset, energy, and communication resources are also diverse among the users. It is demonstrated that SL is more communication-efficient than FL in the scenarios of large model size and small local dataset [80], and the communication overhead of which depends on the user's local dataset size. To this end, a new distributed learning architecture relying on a hybrid learning technique could be a better solution, which uses the idea to benefit from different learning algorithms according to the users' unique characteristics. For instance, an HFCL framework was proposed to let the users incapable of sufficient computational power deploy CL while the rest use FL [11]. In [81], a Split Federated Learning (SFL) was proposed to combine the parallel model training mechanism of FL and the network splitting structure of SL, which is beneficial for a resource-constrained environment where full model training and deployment are not feasible at the local users. In our recent work, we further propose an HSFL architecture in which the users with small data size and weak computational capability are allowed to choose SL while the others use FL [12]. In the following, two hybrid distributed learning architectures are introduced.

#### 1) HFCL ALGORITHM

FL algorithms bring the learning tasks to the edge level, wherein the users are required to be computationally powerful since they have to train the full ML model. However, this requirement may not always be satisfied due to the diverse computational capabilities of the users. In [11], [82], the authors proposed an HFCL framework to train ML models efficiently exploiting the computational capabilities of the users, which is achieved by only letting the users that have enough computational resources employ FL while the other users resort to CL by transmitting their local raw dataset to the BS. The learning mechanism of the HFCL framework is illustrated in Fig. 11.

In HFCL, the users are grouped into active and passive user sets depending on their computational capabilities to

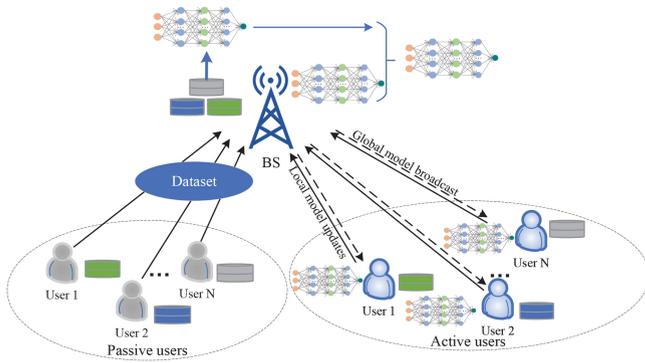


FIGURE 11. The learning mechanism of HFCL framework.

either perform CL or FL, respectively. In this case, the passive users transmit their local datasets to the parameter server which then uses them to train the ML model. On the other hand, the active users upload the gradient information calculated locally based on their private datasets. Next, the parameter server performs model aggregation with the computed gradients from users and the parameter server itself and then sends the updated model parameters back to the active users. The HFCL faces the challenge that the active users need to wait for the passive users to complete their data transmission at the beginning of the model training, followed by the model aggregation at the parameter server before they can update their local model parameters. To address this problem, the authors proposed a sequential dataset transmission approach where the local datasets of the passive users are divided into smaller blocks so that both active and passive users can perform gradients and data transmission during the same communication round.

## 2) HSFL ALGORITHM

In [80], the authors demonstrated that the FL is more communication-efficient and computation-efficient when the users have large local datasets and the model size is small, otherwise, SL is more efficient [80]. Moreover, the user-side computational cost in SL is significantly reduced compared to FL because of the network splitting structure. The disadvantages of FL are that each user needs to train a full ML model but some resource-constrained users cannot afford that and that both the server and users have full access to the local and global models which causes privacy concerns from the model's privacy perspective. On the other side, the disadvantages of SL are that only one user engages with the server at one time while the others stay idle, causing a significant increase in the training period. To address these issues in FL and SL, SFL was proposed to exploit the advantages of FL and SL [81]. The architecture of SFL is presented in Fig. 12.

In Fig. 12, the full ML model is divided into two parts by the cut layer, one is the user-side model residing at the users and the other one is the BS-side model residing at the BS. All the users carry out forward propagation through

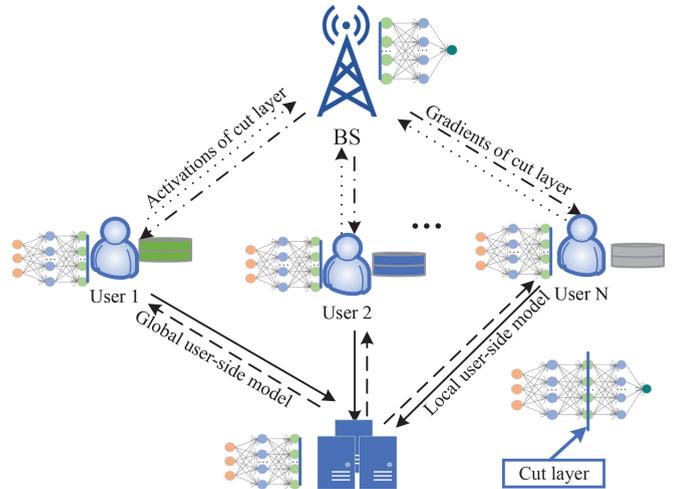


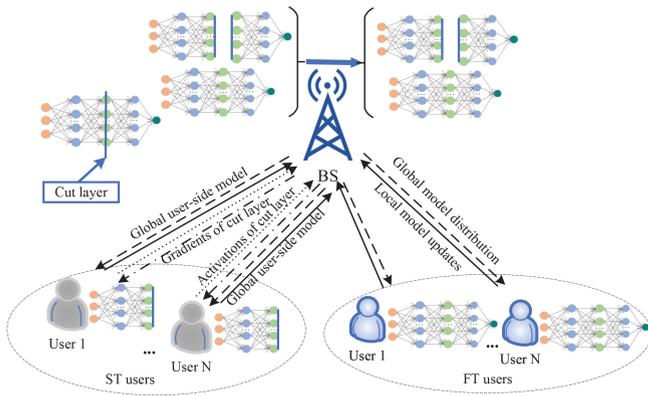
FIGURE 12. The learning mechanism of the SFL algorithm.

the user-side model with their local datasets in parallel and pass the activations of the cut layer to the BS. The BS then conducts forward propagation and backpropagation on the BS-side model with the received activations from each user separately in parallel. Then, it computes the gradients of the cut layer and sends them back to the respective users for calculating the gradients of user-side models. Afterward, the BS updates its BS-side model using *FedAvg*, and the user-side model updates are sent to a fed server for model aggregation using *FedAvg*. With the parallel training architecture, the SFL shortens the training time in SL and achieves similar performance to SL in terms of test accuracy and communication efficiency. By using the network splitting structure, it has better communication efficiency than FL when the users have small local datasets, and it has better model privacy than FL because the users/BS cannot access the BS-side/user-side model except for some smashed data of the cut layer.

However, the SFL algorithm still experiences high communication overhead as in SL when the users have large local datasets since the training dataset could be highly imbalanced and distributed over the users. Fortunately, this issue can be compensated by letting some users use FL which is more communication efficient than SL in this scenario. Based on the works in [80], [81], we propose an HSFL framework that also aims to seek the advantages of FL and SL, and it can eliminate the drawbacks of SFL [12]. The HSFL adopts the same parallel model training mechanism as FL and the same network splitting structure as SL, but it has a different architecture from SFL. The illustration of the architecture for HSFL is shown in Fig. 13. In HSFL, the users are allowed to choose either FL or SL method according to their own unique characteristics, such as the users with small datasets and powerful computational capabilities would prefer FL in which the users run a full ML model locally, and the users with large dataset and weak computational capabilities would resort to SL wherein the users only run a part of the full

**TABLE 3.** Comparisons of different distributed learning architectures.

Distributed learning architecture	Characteristics	Training mechanism	Communication overhead	Computing ability requirements	Ref.
FL	A full model at local for all the users	Parallel	Model parameters	High at local	[10]
SL	A sub-model at local, another at the BS for all the users	Sequential	Smashed data (activations and gradients of the cut layer)	Low at local	[76]
SFL	A sub-model at local, another at the BS for all the users	Parallel	Smashed data	Low at local	[81]
HFCL	Central users: a full model at BS; Federated users: a full model at local	Central users: Training together at BS; Federated users: Parallel	Central users: Raw dataset; Federated users: Model parameters	Very low for central users; High for federated users	[11]
HSFL	Split users: a sub-model at local while another sub-model at BS; Federated users: a full model at local	Split users: Parallel by collaborating with BS; Federated users: Parallel at local	Split users: Smashed data; Federated users: Model parameters	Low for split users; High for federated users	[12], [13]


**FIGURE 13.** The learning mechanism of the HSFL framework.

ML model locally while the server runs the remaining part of the ML model.

During the training process, the BS initializes the architectures and weights of the global full ML model and also divides a copy of it into two sub-models as the global user-side model and the global BS-side model. The users choosing the SL method receives the global user-side model, while the users choosing FL receives the global full model, and then they respectively compute their local gradients with their local datasets in parallel. Specifically, the users choosing SL follows the same rule as SL to train the full ML model by engaging with the BS. Afterward, the users compute their local gradients and send them to the BS which then performs model aggregation with the received local model updates and the updates of its own BS-side model. Later, it sends the updated global full model back to the users choosing FL and the updated global user-side model to the users choosing SL, respectively. The challenge of HSFL is

how to decide which learning method, i.e., SL or FL, for each user. We further design a metric to measure the characteristics of each user, called the diversity index, which is defined as the weighted sum of four parameters, including computational capability, dataset size, dataset diversity, and user diversity. Considering the scenario of deploying HSFL in wireless networks, we formulate the learning method selection and user selection problem as a Multiple-Choice Knapsack Problem (MCKP) and propose an energy-efficient user scheduling algorithm [19] to select a subset of users in each communication round and schedule each user with either the SL or FL method.

As discussed above, state-of-the-art distributed learning architectures have their unique characteristics and can be efficiently used in specific application scenarios. In Table 3, we summarize the comparisons of different distributed learning architectures. Moreover, the convergence performance of implementing different distributed learning architectures in wireless networks with the best channel user scheduling scheme under non-IID data is shown in Fig. 14.

## B. ASYNCHRONOUS DISTRIBUTED LEARNING FOR HETEROGENEOUS WIRELESS NETWORKS

Due to the heterogeneity of the users with different computational capacities and energy resources, the local computation of each user does not complete at the same time. Moreover, the wireless network is always heterogeneous in terms of each user accessing diverse spectrum resources and suffering dynamic wireless channels for the transmission of model parameters. In most studies of distributed learning, the model aggregation at the parameter server is assumed to be synchronous. However, in this case, the server has to wait for the stragglers, i.e., the slow users, before performing model aggregation. Thus, research on asynchronous optimization

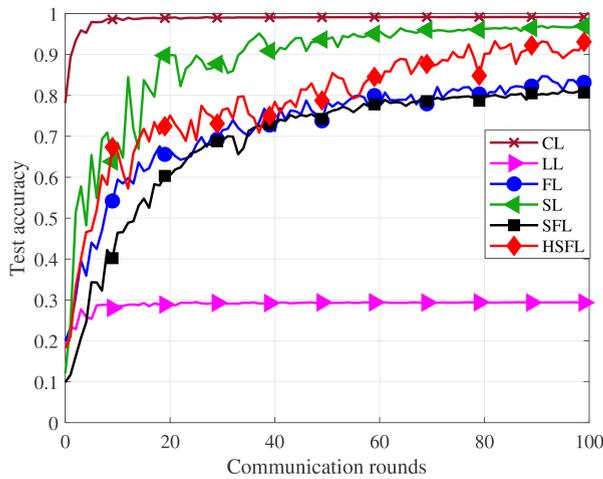


FIGURE 14. The learning accuracy performance of different distributed learning architectures.

methods has gained significant attention to solve the straggler problems in distributed learning.

### 1) THE ISSUES OF CLASSICAL FL IN WIRELESS NETWORKS

Recently, FL has received significant achievements to train a global model on datasets partitioned across a number of users, which exploits a large amount of training data from diverse users and provides privacy preservation for them. However, when applying the classical FL to resource-constrained users, a few issues are emerged as follows:

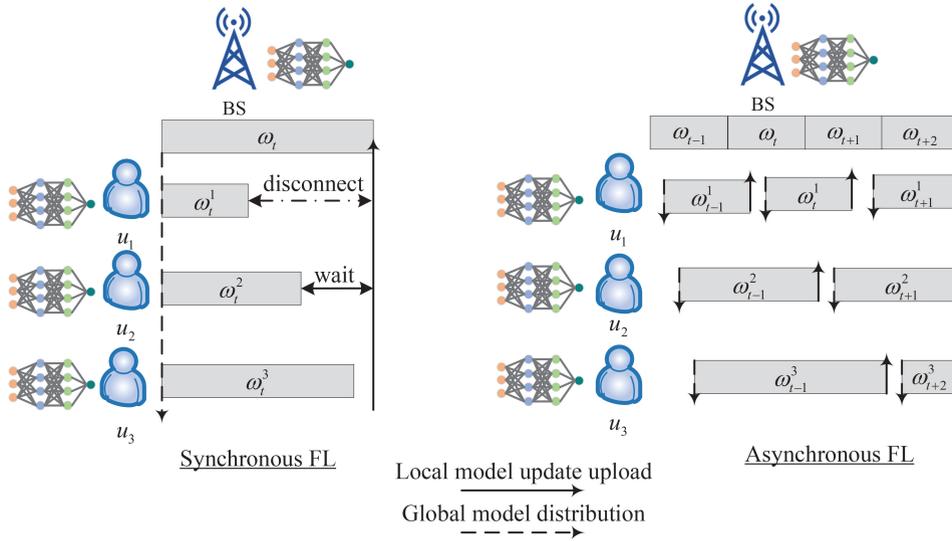
- **Heterogeneity:** The heterogeneity of users in terms of different computation capacities, datasets, and wireless channel conditions causes different completion times of local gradient computation, so the aggregation server has to wait for the slow users.
- **Unreliability:** The selected users may go offline unexpectedly due to their unreliability, which also causes the aggregation server to wait for the local gradients from the unreliable users.
- **Low round efficiency:** Due to the heterogeneity of user diversity (different computational abilities and channel conditions of users) and data diversity (training dataset size and distribution over users), the users who finish local gradient updates early have to wait for those straggler users in each training round.
- **Low resource utilization:** Due to limited spectrum resources and inefficient user scheduling algorithms, some competent users may be rarely selected.
- **Security and privacy concerns:** There are several attacks that can compromise the security of classic FL, including poisoning and backdoor attacks. The privacy concern comes from the possible data leakage during the training process.

To overcome the above-identified challenges, asynchronous training has been widely studied in traditional

distributed SGD, known as asynchronous stochastic gradient descent, for stragglers and heterogeneous latency [83]. The authors in [83] first developed an asynchronous stochastic gradient descent procedure, Downpour SGD, to train large-scale ML models distributively. Downpour SGD builds multiple replicas of a single DistBelief model and divides the training data into a number of subsets and then runs a copy of the model on each of these subsets. It leverages the concept of a centralized sharded parameter server, through which the models can exchange their updates. This approach is asynchronous in the aspects that the model replicas run independently of each other and the parameter server shards also run independently of one another. Compared to synchronous SGD where one user failure will delay the entire training process, Downpour SGD is more robust to user failures since the other model replicas continue the training processing even if one user in a model replica fails. Asynchronous FL was first studied in [84] by taking advantage of asynchronous training and combining it with federated optimization. In asynchronous FL, the BS server can perform model aggregation once it receives any local model updates from the users without the need of waiting for the lagging users shown in Fig. 15. Due to the asynchrony of completing local model updates by the users, the local model updates uploaded in the same round may contain different fresh information and possess varying degrees of staleness because the local models are trained by using the global model versions received from different time periods. Moreover, the diversity of channel conditions causes the transmission of local model updates from different users asynchronous. Therefore, it is essential to design an effective and efficient asynchronous FL algorithm in wireless networks that could deal with the staleness in the system appropriately with restricted communication resources.

### 2) ASYNCHRONOUS FL IN WIRELESS NETWORKS

The contradiction between the limited wireless resources and the explosive growth of the number of users is gradually intensifying nowadays, making it unrealistic to deploy a strictly synchronous FL system composed of a massive number of users with great heterogeneity over the wireless networks [85]. On one hand, a massive number of users trying to upload model parameters simultaneously will bring high communication overhead and cause congestion in the network. On the other hand, the BS can only perform model aggregation until all the local model updates from all the users are received, but some users with poor communication conditions and weak computational capabilities can greatly lag the training process, leading to extremely low training efficiency. Thus, an asynchronous FL could be much more scalable and applicable in wireless networks. In this case, the local model updates trained from the same global model can be transmitted in different time slots, which can greatly reduce the instantaneous communication load. Additionally, the BS can perform global model updates whenever it receives local model updates without having to


**FIGURE 15.** The training procedures of synchronous vs. asynchronous FL.

**TABLE 4.** The architectures of asynchronous FL.

The architecture of asynchronous FL	Working principles	Challenges	Advantages	Ref.
Classic Asynchronous FL	Aggregation once receives the local updates	High communication overhead, aggregation server crash	No need to wait	[84]
Semi-asynchronous FL	Aggregation after a specific period of time	Performance degradation by slow users	Alleviate the effects of the straggler users	[86]
Clustered asynchronous FL	Users are clustered into groups, Inner-group and inter-group aggregation	The clustering algorithm and metrics	Increase training efficiency	[87]

wait for the updates from all the users, which significantly improves the overall training efficiency.

### 3) HIERARCHICAL ARCHITECTURE OF ASYNCHRONOUS FL

In [84], a *FedAsync* algorithm which combines a function of staleness with asynchronous update protocol was developed. However, the users have to transmit a large amount of data to the server, which may cause the server to crash. Moreover, the stale local updates from the stragglers can decrease the accuracy of the global model to a certain extent. To this end, researchers have developed two schemes to address these challenges, semi-asynchronous FL and cluster FL [87]. In Table 4, we summarize the characteristics of different asynchronous FL architectures.

The semi-asynchronous FL combines the classic FL and asynchronous FL, in which the aggregation server caches some local updates that arrive early and aggregates them after a specific period of time, which then can alleviate the effects of the straggler users. A data expansion method was used to alleviate the straggler phenomenon in [88], in which a

semi-asynchronous communication method was proposed to speed up convergence for FL. In [86], a new energy-efficient semi-synchronous FL was proposed, which aggregates the local updates at a specific time interval determined by the slowest user.

Cluster FL is an effective approach to increase the training efficiency with reduce the transmission data from local users by grouping together users with similar performance, functionalities, or datasets [87]. To reduce the network congestion caused by a massive number of users simultaneously uploading local model updates in edge computing networks, the authors in [89] proposed a cluster-based FL mechanism. This mechanism divides users into different clusters, where users in one cluster transmit their local model updates to the cluster head for synchronous model aggregation while all cluster heads communicate with the edge server for global aggregation in an asynchronous way. A cluster-based asynchronous FL framework adopting an appropriate time-weighted inter-cluster aggregation strategy was proposed in [90], which eliminated the straggler effect and improved learning efficiency.

#### 4) USER SCHEDULING AND RESOURCE ALLOCATION FOR ASYNCHRONOUS FL

Recent studies have put considerable attention on device scheduling and resource allocation for asynchronous FL [15], [74], [91]. In [15], the transmission scheduling scheme considering time-varying channels over multiple rounds, and stochastic data arrivals of the edge devices with asynchronous FL was first studied. The authors developed an asynchronous learning-aware transmission scheduling (ALS) algorithm for the scenario with the perfect statistical information about the system uncertainties and further proposed a Bayesian ALS algorithm to learn the system uncertainties without requiring any prior information or requiring only partially observable information. Furthermore, three device scheduling schemes, namely random, significance-based, and frequency-based scheduling, were investigated for the heterogeneous wireless networks by adopting the asynchronous FL framework with periodic aggregation [74]. An RL-based device selection, UAVs placement, and resource management algorithm were developed for deploying the asynchronous FL framework in multi-UAV-enabled networks [91], in which it also demonstrated that the proposed asynchronous online FL is particularly useful for streaming data with heterogeneous devices having different computing capabilities and communication conditions [54].

#### 5) SECURITY AND PRIVACY IN ASYNCHRONOUS FL FRAMEWORK

To ensure the security required by FL, a blockchain network is introduced into the FL framework to replace the classic central server to aggregate the global model, which avoids real-world issues such as interruption by abnormal local user training failure, dedicated attacks, etc. Researchers studied blockchain-enabled asynchronous FL framework by exploiting the decentralized property of blockchain network and the fast convergence performance of asynchronous FL strategy [92], this framework improved training efficiency and prevented poisoning attacks. In [93], the authors studied the blockchain-enabled asynchronous FL framework to mitigate the threats of poisoning attacks against IoT anomaly detection models and then devised a novel Generative Adversarial Network (GAN)-driven differentially private algorithm by injecting controllable noise into local model parameters.

### C. INCENTIVE MECHANISMS OF USERS FOR PARTICIPATING FL PROCESS

Generally, to implement distributed learning architectures, all the users are assumed to voluntarily participate in global model aggregation without requiring any returns. However, in practice, the participants may be reluctant to participate in this federation process without receiving compensation since training ML models is resource-consuming [94]. In [95], the incentive mechanism in FL was first studied by providing an incentive-compatible scoring system for building a payment

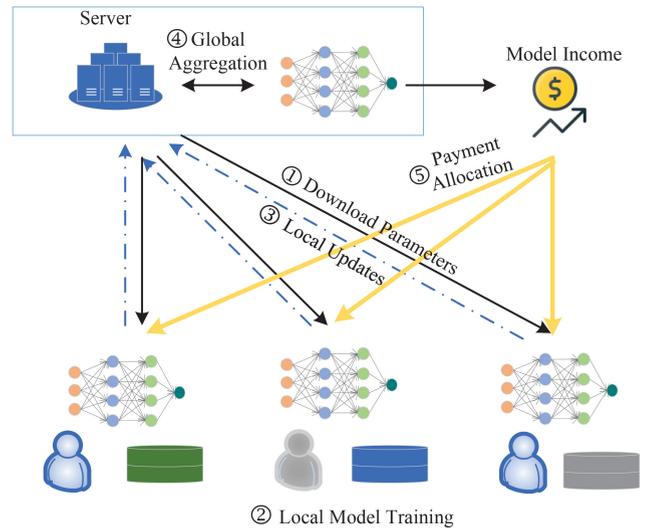


FIGURE 16. The architecture of incentive mechanism.

system. Fig. 16 shows the architecture of the incentive mechanism in FL, in which the users might be mobile devices, edge nodes, and IoT devices in cross-device FL or giant companies in cross-silo FL. They provide various types of resources instead of only data, all of which are key factors to the training performance. After global model aggregation, the server will pay each user according to their individual contributions to the FL process. In [14], [94], the authors did comprehensive surveys of incentive mechanisms for FL in recent research works. They identified the challenges of incentive mechanism design for FL and then summarized a taxonomy of existing incentive mechanisms for FL in terms of main techniques, such as Stackelberg game [96], [97], auction [98], contract theory [99], [100], Shapley value [101], RL [102], and blockchain [103]. The Stackelberg game, auction, and contract theory are mainly employed to perform user selection and payment allocation for incentivizing users to participate in FL process, while the Shapley value is used for a fair assessment of FL user contribution. Both RL and blockchain are introduced to improve the performance and robustness of the incentive schemes.

#### 1) THE RELUCTANCE OF USERS

First, the FL process consumes resources including computational power, bandwidth, and private data, from participants, some of which might be constrained in scenarios like mobile networks and MEC systems. Moreover, privacy and security concerns are raised because the FL server can infer the important information of the training data [14]. In [104], the authors showed that many participants gain no benefit from FL because the federated model is less accurate on their data than the models they can train locally on their own, which removes their main incentive to join the FL process. To this end, without proper incentives, the users tend to opt out of the participation, may contribute either uninformative

or outdated information, or even contribute malicious model information.

## 2) INCENTIVE MECHANISM FOR FL IN HETEROGENEOUS NETWORKS

When deploying FL in wireless edge networks, the users, like mobile phones, IoT devices and drones, are always heterogeneous with different computational capacities, training data size, power, and communication resources, and this heterogeneity might degrade the performance of FL. Hence, the incentive mechanism design for FL in wireless edge networks should encourage more high-quality users to participate in the FL process so as to eventually improve the convergence performance of FL. In [99], reputation is applied as the metric to select reliable users for participating in FL and is calculated in a decentralized manner through the consortium blockchain; the incentive mechanism using contract theory was proposed to stimulate high-reputation workers with high-quality data to join in model training. Besides, the proposed scheme should not introduce much computational cost and communication overhead since these resources are constrained at some users. In [97], a Stackelberg game-based incentive mechanism was proposed to select a set of IoT devices willing to join the model training process while minimizing the overall training costs, i.e., computational and communication costs. Taking into account the non-IID data and the wireless channel constraints, an auction mechanism was designed to realize the trading between the FL server and the users for pricing and task allocation [98]. In addition, a multi-dimensional contract-matching-based incentive mechanism was designed to address the incentive mismatches and information asymmetry between the UAVs and the FL server [100]. Due to the special challenges of unshared decisions and difficulties of contribution evaluation for FL in IoT applications, the DRL algorithm was exploited to learn system states from historical training records and adjust the strategies of the parameter server and edge nodes according to the environmental changes [102].

## D. DISCUSSION AND OUTLOOK

Table 3 summarizes all the above-mentioned distributed learning architectures. We can observe that each distributed learning technique has a unique advantage in terms of communication efficiency and computation efficiency, while the HSFL technique can achieve a trade-off between them. However, scheduling each user with the proper learning method efficiently is still in its fancy.

Asynchronous distributed learning is an effective approach to address the straggler issue that appeared in classical distributed learning techniques due to the diverse computational capacities of the users. However, the study of asynchronous distributed learning still requires more attention from both academia and industrial partners since its more suitable for practical use, particularly special attention is needed when deploying in wireless networks due to unreliable wireless communication links. Moreover, it is also necessary to design

an asynchronous learning scheme for the hybrid distributed learning architectures since the users with different learning methods complete their local learning at a different pace. The potential solution is to group the users completing at a similar pace into one cluster, and then perform inner-cluster synchronous aggregation and inter-cluster asynchronous aggregation. In this case, the clustering algorithm, especially the clustering index, needs careful design.

Another important issue to be addressed is the design of incentive mechanisms for the users to join in model aggregation. The users want to get involved in model aggregation only if they can receive either economical compensation or local model improvement. Hence, an effective reward mechanism needs to be designed to motivate more high-quality users to participate in model aggregation. Particularly, the metrics that can measure the quality of the users are required, such as reputation [99], training costs [97], and dataset quality.

## IV. AI-ENABLED EDGE COMPUTING

Edge computing has been proposed as a promising solution to handle data processing of a large volume of security-critical and time-sensitive data. With the distributed deployment of edge devices, edge computing can shift computational and caching capabilities from distant and centralized clouds to the network edge. This enables AI-based data analytics to be performed in a distributed manner, and thus support ubiquitous AI services. However, the edge devices are typically resource-constrained and have heterogeneous computation capabilities, thereby causing critical challenges in resource management and wireless caching [105], [106]. In addition, with the increasingly powerful chips integrated at the local devices, they are able to handle some simple computational tasks. Thus, deciding which task should be offloaded to the edge, how much power is used to transmit the data, and when and where (i.e., in multiple edge devices) the task is offloaded, is necessary and full of challenges. Recently, many researchers [45], [46] have put much attention to this problem from the aspect of optimizing computation offloading scheme and resource allocation, with the proposed algorithms based on convex optimization, Lyapunov optimization, game theory, and ML techniques.

Computation offloading plays an important role in edge computing, and it provides a paradigm of appropriately allocating computation resources between different layers (e.g., wireless networks normally consist of three-layer architecture that includes local, edge, and cloud layers) [7]. Efficient edge computing relies on the edge device or the end devices making optimal decisions on computation offloading and resource allocation. Conventional centralized computation offloading methods require complete and accurate network information so that the edge device can make optimal decisions on which users offload their data while others execute data processing locally, and achieve optimal resource allocation based on the obtained prior network information [49]. The joint computation offloading and resource allocation

TABLE 5. Comparisons of ML techniques and traditional method-based offloading algorithms.

Offloading algorithms	Characteristics	Dataset	Complexity	Ref.
Traditional	Game theory, Lyapunov optimization	Not need dataset	High algorithm complexity, especially multiuser multi-server	[45], [46]
DRL	Consider computation offloading as MDP	Collect dataset while training	High time complexity	[53], [54]
Multi-agent RL	Consider multi-user computation offloading as Markov Game, parallel training	Each user collects its own dataset while training	Depends on the complexity of each DRL agent	[113], [114]
DL	Formulate computation offloading as multi-label classification problem	Generate dataset before training	Depends on offline training complexity	[111], [115]
Imitation Learning	Mimic expert behaviours	Generate expert dataset	Depends on offline training complexity	[112], [116]

problems are often modeled as combinatorial optimization problems with non-linear constraints that are difficult to optimize efficiently using traditional optimization methods. Therefore, in [107], [108], the authors leveraged the RL techniques to extract valuable knowledge from the environment and then to make adaptive decisions, and hence they offered distributed computation offloading policy and optimal resource allocation for the end users without the need for a priori knowledge of network statistics.

The above studies focus on centralized intelligent approaches for computation offloading, which model the sophisticated global optimization the problem as a single-agent RL problem that requires a central agent to collect the global state information of the environment to make global decisions for the entire system. This becomes challenging when the number of users increases. Moreover, in edge computing-enabled wireless networks, the computation offloading problem involves the interaction among multiple decentralized users, wherein each user is considered an intelligent agent and can make its decisions individually based on its local observation of the environment. Since the single-agent RL only learns a decision-making rule for one user without considering the influences of the existence of other users on its behaviors, the multi-agent RL is investigated to solve the decision-making problems with more than one agent coexisting in a shared environment [109], [110]. Next, we present an overview of using RL techniques to optimize computation offloading schemes and resource allocation solutions from single-agent RL to multi-agent RL algorithm for computation offloading, and also the approach of introducing FL into RL technique as FRL is discussed to address the multi-user computation offloading problem. Moreover, other machine learning techniques, such as DL technique and imitation learning, have also been investigated to learn computation offloading strategies [111], [112]. The comparisons of different machine learning techniques and traditional mathematical algorithms for computation offloading are summarized in Table 5.

### A. DRL FOR COMPUTATION OFFLOADING

To address the problem of optimal computation offloading and efficient resource allocation, the conventional method formulates this joint problem as either a convex optimization or mixed-integer problem, but this finite-time optimization has the drawback that the computation offloading parameters are considered to be irrelevant under different system states. In this case, the long-term performance over dynamic system states changing is not maintained [46], [117]. MDP is an effective mathematical tool to model the impact of users' actions in a dynamic environment, and it allows for seeking the optimal action for achieving a particular long-term goal. To this end, the optimization of computation offloading policy under a dynamic environment can be modeled by MDP. When modeling the computation offloading problem as an MDP problem, a state transition probability matrix that describes the system dynamics needs to be constructed to obtain the optimal offloading policy. However, the system dynamics are hard to measure or model in most real-world scenarios, and thus obtaining the state transition probability matrix is intractable, especially when the state and action spaces are large [118].

RL techniques have been used as promising solutions to tackle this challenge based on the trial-and-error rule, where the RL agent, i.e., the user, can adjust its policy to achieve the best long-term goal according to the future reward feedback from the environment without prior knowledge of system models. In [108], [119], the authors investigated the dynamic computation offloading process and developed RL algorithms to learn the optimal offloading mechanism with the goal of minimizing latency and choosing the energy-efficient edge server. Besides, the DRL algorithm has been proven to be more effective for enabling RL to handle large state spaces by leveraging the powerful DNNs to approximate state-action values, which is envisioned to solve complex sequential decision-making problems. Therefore, DRL is particularly suitable for solving computation offloading problems in a dynamic environment. First, DRL can target the optimization

of long-term offloading performance, which outperforms the one-shot and greedy application of the approaches studied in static environments. Second, the optimal offloading policies can be obtained without any prior information on the system dynamics (e.g., wireless channel or task arrival characteristics) by using the DRL techniques. Third, thanks to the powerful representation capability of the DNN, the optimal offloading policy can be adequately approximated even in complicated problems with vast state and/or action spaces [118].

Recently, many researchers have investigated the DRL techniques to learn the optimal offloading mechanisms and at the same time optimize resource allocation [53], [54]. In [54], the authors first proposed a DQN-based algorithm to learn the optimal computation offloading policy, in which the high dimensional state spaces were handled. In [120], a DRL algorithm was implemented to learn optimal decisions on resource allocation for vehicular edge computing networks, where the DQN is improved by applying dropout regularization and double DQN. Besides, the joint computation offloading and resource allocation problem has also been formulated and solved with DRL algorithms in recent studies [53], [121], [122]. The authors in [53] jointly optimized the offloading decision and computational resource allocation to minimize the sum cost of the MEC system. In [121], a DRL framework was proposed to jointly optimize the offloading decisions and resource allocation with the goal of minimizing the weighted sum of users' energy consumption and task execution latency. In [122], a DRL-based online offloading framework was proposed for a wireless-powered MEC network to obtain optimal task offloading decisions and wireless resource allocations under the time-varying wireless channel conditions. The authors in [123] investigated the optimal task offloading policy, computation, and communication resource allocation, by the proposed intelligent resource allocation framework based on a multitask DRL algorithm. Moreover, in [124], the authors proposed the DRL-based algorithm for joint edge server selection, optimization of offloading decision, and handover in a multi-access edge wireless network. Specifically, in [125], the authors combined the advantages of Lyapunov optimization and DRL algorithms and proposed a novel online stable offloading framework that achieves making joint action of binary computation offloading and resource allocation in each short time frame without the assumption of knowing the future realizations of random channel conditions and data arrivals. In [126], the Meta-RL (MRL) algorithm was proposed to address computation offloading problems, so new users can learn their offloading policies fast based on their local data and meta policies. Additionally, the MRL training in the MEC system can leverage resources from both the MEC server and the users.

However, the above research works rely on centralized decision-making at the server, which limits the scalability of most RL-based algorithms due to the huge decision space and the overwhelming information collection from

the MEC system. Moreover, implementing DRL into computation offloading optimization problems needs numerous interactions with training environments to obtain experiences with large quantities and high diversity, which causes huge costs due to the trial-and-error process (also known as exploration costs). Thus, the huge training cost lies in training a high-performance DRL agent for the MEC system, which is often unaffordable for a single MEC environment. To address this challenge, the authors in [127] proposed a distributed and collective DRL-based algorithm to adaptively learn the offloading and channel allocation decisions. Based on exploring the domain of distributed DRL training [128], the proposed algorithm assimilates experiences and knowledge from multiple MEC environments to obtain a collective DRL agent with high performance by adopting the experience-sharing scheme between the master agent and distributed agents, and thus the cost of the trial-and-error process is spread over the distributed system.

The aforementioned centralized offloading algorithm is restricted by the increasing scale of the network and is the inability to observe the local environments, and it also causes huge costs for the edge server. The distributed offloading is explored from the following two cases: a) a distributed DRL algorithm that enables each user to make its offloading decision without knowing the task models and offloading decisions of other users, which still relies on the broadcast information from the edge server in each time slot [129], b) a distributed DRL training is proposed to train collective DRL agents by assimilating experiences from multiple MEC environment [127], which not only exploits the distributed computational resources of multiple MEC servers but also obtains more diverse training data. However, both of the distributed offloading approaches does not discuss the scenario where multiple users make offloading decisions together while sharing the computational and communication resources. This is more practical in the real world since when one user is making their own offloading decisions, other users are also making their decisions and thus affect the decision-making of the user. Therefore, distributed offloading considering the competitive behaviors among the users needs to be studied.

## B. MULTI-AGENT RL FOR COMPUTATION OFFLOADING

When there are multiple users making decisions simultaneously in an edge computing system, each user's decisions are affected by the other users' decisions, so the degree of cooperation plays a vital role in the design of computation offloading policies. In this multi-agent system, each user is regarded as an agent that can only observe its local environment information. At each time point of observation, the edge computing system is in a system state, each agent takes an action according to the computation offloading policy of all the users in a vector form, and then the system responds to their actions by moving to a new system state according to the probability distribution and sending the rewards to

each agent. This multi-agent edge computing system models more practical computation offloading scenarios where more than one agent makes decisions together to achieve goals, which may be cooperative or in conflict with each other. Compared to the single-agent computation offloading problem that falls under a category of single-agent RL and can be solved by the popular RL algorithms, like Q-learning and DQN, this multi-agent computation offloading problem falls under the category of multi-agent RL [130].

Due to the simultaneous learning of multiple agents, it is challenging to solve the formulated multi-agent RL computation offloading framework. Recently, researchers have put much more attention to investigating this problem by proposing algorithms to solve it in a centralized or decentralized manner. In the centralized approach, a central trainer collects the reward information from the individual agents and dispatches the actions to them. In [131], the BSs are considered as the agents to execute RL independently for obtaining the Q-values, and then the Q-values are shared with new BSs as cooperative learning. With a similar information-sharing mechanism, a distributively executed dynamic power allocation scheme was developed by using deep Q-learning, which is suitable for large-scale networks [114]. This is based on a distributed framework with a centralized training assumption, in which the BS trains a single DQN using the transitions collected from all agents, while each agent has the same copy of the DQN parameters for decentralized execution. However, this approach becomes impractical as the number of agents increases. Therefore, a decentralized framework where each agent independently learns its own strategy to maximize individual return was proposed, which is able to deal with large-scale networks. In [113], an independent learner-based multi-agent Q-learning was proposed by considering the other users as part of the environment, in which each user is modeled as an RL agent observing its local environment information to independently learn a task offloading strategy that minimizes its energy consumption and task execution latency. While the Independent Q-learning (IQL) algorithm [69] avoids the scalability problems of centralized algorithm and works well in practice as shown by empirical evidence, it faces the challenges of a non-stationary environment from the point of view of each agent as it contains other agents who are also learning themselves.

Therefore, the distributed multi-agent RL schemes with collaborations among users were investigated to address this challenge. A distributed multi-agent DRL scheme with a collaborative exploration of the environment was proposed to solve the joint problem of computation offloading and resource allocation [132]. The agents independently learn their individual strategies based on their local observations and refine their learned strategies through a learning process driven by the specially designed reward function. In [133], the proposed decentralized multi-agent RL algorithm solves the computation offloading problem with the agents sharing

their estimate of the value function with each other at the critic step. Unfortunately, the information sharing among users causes high communication overhead and is even infeasible due to the large-scale deployment of a beyond 5G network. To address those challenges, a distributed ML-agent RL framework without information sharing among users in the MEC system was studied in [117], [134]. In [117], each user independently learns its computation offloading policy by forming and updating conjectures on the behaviors of other users using the historical information retrieved from the BS. In [134], each Cloud Center (CC) is considered as an agent, where each CC determines the task offloading strategy independently by learning explicit models of other CCs as stationary distributions over their actions. Additionally, RNN architecture was studied to improve the offloading strategy when the multi-agent RL algorithm is applied [135], [136]. A Long Short-Term Memory (LSTM) network was introduced in the multi-agent DDPG network to accurately estimate the current state information of the MEC system in [135]. The LSTM technique combined with the DQN could overcome the partial observability and the curse of high dimensionality in local network state space faced by each vehicle user pair for packet scheduling and resource management in vehicular networks [136]. In [137], the authors formulated the dynamic decentralized computation offloading game as a multi-agent Partially Observable Markov Decision Process (POMDP), and then they designed an algorithm that can achieve the optimal offloading strategy by combining policy gradient DRL-based approach with DNC. DNC is a special recurrent neural network and is capable of learning and remembering the past hidden states of inputs. Moreover, the authors in [130] considered the practical challenges of deploying the previously mentioned deep multi-agent RL algorithms and studied applying them to solve task offloading with reward uncertainty.

### C. FRL FOR COMPUTATION OFFLOADING

FRL was first studied in [138], which built a MultiLayer Perceptron (MLP) as the shared value network to compute a global Q-network output with its own Q-network output and the encrypted output of Q-networks from other agents. RL has the problem of learning efficiency caused by low sample efficiency. Even though distributed RL can address this problem by sharing information (i.e., raw data, parameters, or gradients) to the central server for model training, there is a possibility of agent information leakage. In a multi-agent system, each user can only observe partial environment information which is not enough for the agent to make decisions. Furthermore, many RL algorithms require pre-training in simulated environments as a prerequisite for application deployment, but the simulated environments cannot accurately reflect the environments of the real world. To this end, FL with the ability of aggregating information can integrate the information from different users and can bridge the simulation-reality gap, and also it can provide privacy

protection. Then, the idea of combining FL with RL, known as FRL, is generated to address the challenges that exist in RL. In FRL, the three dimensions of sample, feature, and label in FL can be replaced by environment, state, and action, respectively [139].

As discussed in the previous sections, RL has been widely exploited to solve computation offloading problems, but the optimal solutions are obtained only with many assumptions of the environment. In the complex computation offloading environment, each user only knows their own information about waiting for tasks and resources and can receive notifications from the BS. Also, each user's decisions on offloading and resource allocation are affected by the others in the same edge system making decisions at the same time. The collected RL training data from one edge system may be not enough to reflect the complex offloading environment, and thus more diverse data from multiple edge systems are required to be integrated for obtaining complete environment information. Moreover, it is still challenging to implement the trained RL by the proposed algorithms in the aforementioned research work for solving practical computation offloading problems due to the time-varying wireless channels, limited resources, and randomly generated computational tasks. As a result, FL has been introduced in RL-based computation offloading algorithms to address the above challenges with its ability of information aggregation.

In [140], the authors first applied the FL framework to train the DRL agents for intelligent joint resource management of communication and computation in MEC systems. With FL, the DRL agents are efficiently trained in a distributed fashion, and they can handle unbalanced and non-IID data and cope with privacy issues. In [141], the FL was used to conduct the training process of DRL agents for optimizing decision-making about computation offloading and energy allocation in IoT edge computing networks. Moreover, in [132], [142], the FL framework was introduced to train the multi-agent RL algorithm. A distributed multi-Agent DDPG (MADDPG)-based joint hierarchical offloading and resource allocation algorithm was proposed to exploit the FL to train multi-agent deep RL model in Cybertwin networks, which solves the sensitive information leakage issue and relieves the computational pressure at the edge. In [132], each Small Base Station (SBS) adopts an independent learning algorithm while treating the agents as part of the environment in the formulated multi-agent DRL framework, and then the SBSs exchange their model parameters with each other. Finally, each SBS agent performs model aggregation of FL based on the collected model parameters from the other agents. In [143], an effective radio resource management based on federated Q-learning was proposed to optimize resource allocation for computation offloading in 6G-Vehicle-to-everything (V2X) communications, where the locally trained Q-tables are shared to the vehicle edge center pool for global aggregation.

## **D. OTHER LEARNING TECHNIQUES FOR COMPUTATION OFFLOADING**

### **1) DL FOR COMPUTATION OFFLOADING**

Different from most works discussed in the previous sections, DL has also been exploited to design a dynamic offloading strategy. In [111], the computation offloading problem is formulated as a multi-label classification problem. To obtain the optimal offloading policy, an exhaustive strategy is used to search for the optimal solution in an offline way, and then the obtained solution can be used to train a DNN with the composite state of the edge computing network as the input, and the offloading decision as the output. Likewise, the authors in [115] proposed a DL algorithm to avoid an exhaustive decision-making process by training a DNN over the dataset generated by their mathematical model. By this means, once the DNN is trained, it can be used as a decision-maker for offloading specific components. To solve a heavy burden caused by a massive training dataset in multi-user task offloading problem, a distributed DL-based computation offloading algorithm was proposed by training multiple parallel DNNs with the channel gain as the input and the output as the offloading decision [144].

### **2) IMITATION LEARNING FOR COMPUTATION OFFLOADING**

Another promising ML technique, imitation learning, has also been investigated to design offloading schedules [112], [116]. In [112], a novel deep imitation learning-based offloading scheme has been proposed, the ML model is first trained from learning demonstrations in an offline manner based on behavioral cloning. Then, the near-optimal online offloading decisions can be made at a very fast speed with quick and easy deployment. In [116], a multi-agent imitation learning-based computation offloading algorithm was proposed, which allows multiple learning agents to imitate the behaviors of corresponding experts for good scheduling policies. They designed the expert policies by enabling the experts to obtain full observation of system states and then form the demonstrations including state-action pairs for the learning agent to mimic.

## **E. DISCUSSION AND OUTLOOK**

The aforementioned literature has investigated different ML techniques to design optimal computation offloading strategies with a focus on RL algorithms. Although multi-agent RL and FRL frameworks have been proposed to address multi-user computation offloading problems, obtaining the optimal offloading strategies needs analyzing the collaborations or competitions among users. The solution process is always formulated as a Markov game by finding a Nash Equilibrium (NE) to get the optimal strategy, but it is challenging to find the NE or even the NE does not exist for some complicated problems. Furthermore, the above studies provide good prospects for the application of FRL to edge computing, but there are still many challenges to overcome,

including the adaptive improvement of the algorithm, and the training time of the model from scratch.

Imitation learning is another potential technique to design offloading strategy, which can train an ML model from expert demonstrations in an offline manner and learn a near-optimal offloading policy to make fast online offloading decisions. Compared to RL techniques, it enables easier deployment for practical use. However, it is difficult to obtain the expert dataset and the learning adaptability is bad.

## V. COMMUNICATION-EFFICIENT TECHNOLOGIES FOR DISTRIBUTED LEARNING

In practice, as the trained ML model can become outdated with time, continually updating the model in a time-varying environment is essential. Recently, distributed learning has replaced conventional centralized learning as an effective technique to provide ML model training in a distributed manner by exploiting the computational resources from distributed wireless users. Instead of sharing raw data between the users and the BS as in centralized learning, only model parameters need to be exchanged in distributed learning. When deploying distributed learning in wireless networks, it relies on reliable and high-throughput wireless channels to support the real-time transmission of model parameters. In this way, ML can be treated as the data source transmitted from end to end rather than as the enabler at the end of the system. There are three main reasons that distributed learning has been broadly considered: end users have been empowered with strong computational abilities [145], a huge amount of data distributed at end users which can provide valuable information, and the awareness of data privacy [146]. However, the dynamics of the wireless communication environment strongly affect the performance of ML model training. These challenges drive the researchers to focus on designing more efficient wireless communication techniques for distributed learning.

### A. THE CHALLENGES OF TRADITIONAL COMMUNICATION TECHNOLOGIES

When deploying distributed learning in wireless networks, the qualities of wireless channels determine the convergence performance of ML model training and there are some critical bottleneck problems that need to be addressed when using the current wireless communication techniques to support distributed learning:

- *Communication resource limitation:* Since a huge number of wireless users need to communicate with the central BS back and forth to exchange model parameters for the learning process in a distributed manner, it is urgently necessary to design the optimal resource management solution to tackle the limited communication bandwidth and transmission power [147]. Although more frequency bands, such as mmWave, have been widely introduced to support massive connectivity, vulnerable signal propagation still restrains the reliability of communication due to different kinds of channel fading.

Therefore, optimizing the design of distributed learning algorithms to reduce communication overhead is important. Recent research studies address this optimization problem by reducing either the communication rounds or the transmitted gradients in each round [26].

- *Communication conditions:* Apart from limited communication resources, the wireless channel conditions directly affect whether the BS can receive or decode the local model updates from the users. Specifically, the dynamic fluctuation of the communication channel may strongly distort the transmitted information and result in reducing decoding accuracy at the receiver side [147]. Moreover, the reliability and robustness of the dynamic communication channel are the guarantees of successful information exchange to support distributed learning framework. Hence, it is necessary to develop reliable communication techniques to achieve robust and low-latency communications for the implementation of distributed learning in wireless networks.
- *Computational resource limitation:* Generally, wireless users are powered by capacity-limited batteries, and they have diverse computational capabilities, such as IoT devices equipped with small CPUs, drones, and mobile phones lacking in GPUs. Distributed learning requires the users to undertake some model training tasks, which consume computational, energy, and memory/storage resources of the users. Therefore, it is indispensable to design simple and energy-efficient ML models to simplify the computation process [147] or to improve the distributed learning algorithm to efficiently exploit the diverse computational resources of users.
- *Dynamic network:* In real-world scenarios, the end devices can be both static and mobile. In such time-varying wireless networks, communications can be interrupted, connectivity can be blocked, and data can be outdated. Therefore, distributed learning is facing extreme challenges that are caused by environmental dynamics. Hence, designing more stable training schemes that consider asynchronous collaboration, prediction, or other mechanisms that are suitable to the dynamic networks is one of the emerging issues to be solved [29].
- *Privacy and security concerns:* Although one of the purposes to utilize distributed learning in wireless communication is to preserve data privacy, the model gradients information or outputs transmitted through wireless communication links can still be disclosed and reversely traced, which means the privacy is only partially preserved. This kind of privacy concern is named gradient leakage attacks [148] and membership inference [149]. Similarly, security concern comes out when adversaries launch attacks on heterogeneous devices in the network and cause distributed learning faults [26]. Therefore, the transmission of model parameters has higher requirements on reliable and low-latency wireless communication links since the convergence performance of

the ML model is decided by the performance of wireless communication. The traditional communication technologies, resource allocation, and data transmission methods need to be improved by considering the convergence of the ML model as the performance metrics. In the following, we will investigate state-of-the-art techniques, including over-the-Air Computation (AirComp), gradient compression, and user scheduling and resource allocation, to improve the performance of wireless communication for supporting distributed learning.

## B. USER SCHEDULING AND RESOURCE ALLOCATION

### 1) THE REASONS FOR USER SCHEDULING

The emerging paradigm of FL is to provide a decentralized ML model training approach for a wireless edge network with a large number of resource-constrained mobile devices collecting the training data from their environment [10]. Recently, to obtain a high-performance model with a low-latency training process, many research works [150], [151], [152], [153], [154], [155], [156] have been conducted to investigate user scheduling schemes by addressing the following challenges:

- *Dynamic channel condition:* The dynamic wireless environment cannot always guarantee good channel qualities, the spectrum resources are limited;
- *Heterogeneous computational resources:* The available computational resources of individual users vary over time because of other possible task execution. The heterogeneity of users with different computational capabilities causes straggler effects;
- *Heterogeneous data distribution:* The statistical heterogeneity of different data distributions (i.e., IID, non-IID and imbalanced data) over users leads to the drift of local model updates, and it results in different local updates that are of dissimilar significance to the model convergence [157].

To address the above challenges, recent research works have proposed different metrics to optimize user scheduling for model aggregation.

### 2) THE METRICS OF USER SCHEDULING SCHEME

An intuitive design of the user scheduling scheme is to aggregate as many local model updates as possible from users since the whole dataset is distributed over the users. This can be achieved by optimizing the following metrics.

1) *Metric-The Number of Users:* In [158], three user scheduling policies, including random scheduling, round robin, and proportional fair, were studied in terms of FL convergence rate for wireless networks. The analyses revealed that there exists a trade-off between the number of scheduled users and sub-channel bandwidth in the optimization of FL convergence rate under a fixed amount of available spectrum. In [159], [160], the authors have studied this user selection problem with the goal of maximizing the number of selected users for each round under constrained resources.

2) *Metric-Channel Conditions:* In FL, the convergence performance of the ML model heavily relies on the transmission of model parameters, so the channel conditions are necessary to be considered for user scheduling. In [158], the user scheduling scheme, proportional fair, in terms of channel conditions is studied. The authors in [151] investigated federated learning over wireless fading channels and schedule one user for transmission based on the channel conditions in the proposed user scheduling scheme. Moreover, they generalize it as the best channel scheduling scheme by selecting several users with the best channel gains [161].

3) *Metric-The Importance of Local Model Updates:* Due to the non-IID and imbalanced data distribution over the users, each user is of different significance to the global model update. The authors in [162] proposed a reliable UE selection scheme by considering the reliability of the dataset owned by users. In [151], [152], [163], the authors studied a novel user scheduling scheme by considering both the channel conditions and the importance of the local model updates calculated by the users for implementing FL at wireless edge. In [152], the scheduling policy is derived in closed form to achieve the optimal trade-off between channel quality and the importance of local model updates when scheduling one user in each round. The authors demonstrated that channel-based scheduling shows the lowest testing accuracy performance while the model update-based user scheduling has the best performance for AirComp FL. A trade-off performance is achieved by considering them together [163].

4) *Metric-Age of Update:* The aforementioned user scheduling schemes are focused on either exploiting the limited spectral resources or investigating the diversity of local datasets to maximize the number of updates collectible by the BS in each round of global communication but ignore the staleness of these updates. In [155], a new metric, Age-of-Update (AoU), was proposed to measure the staleness of local model updates in each round, and then a user scheduling algorithm that considered both the straggler effect and the communication quality was developed to minimize the AoU. This scheme aims to keep the collection of all the local updates as fresh as possible while considering fairness among all the users. The authors in [164] considered AoU as the performance metric of user fairness to optimize the user selection policy, transmission power, and CPU-cycle frequency.

### 3) THE OPTIMIZATION OF USER SCHEDULING AND RESOURCE ALLOCATION

Due to resource limitations in wireless networks, including the limited communication resource and the scarce energy resource for the users, the joint user scheduling and resource allocation problem has been studied by a series of works. A joint learning, user scheduling, and resource allocation problem was formulated to optimize the uplink Resource Block (RB) allocation and transmit power allocation so as to decrease the packet error rates of each user and improve the

FL performance in wireless networks [165]. An optimization problem that jointly designs the power allocation and user scheduling scheme for the UAV swarm network were formulated to reduce the FL convergence round [166]. The authors in [167] investigated the optimal user scheduling policy and power allocation scheme with Non-Orthogonal Multiple Access (NOMA)-based FL uplink communication during the entire learning process, and thus the aggregation latency was reduced. In [168], a joint bandwidth allocation and user scheduling problem was formulated to optimize the convergence rate of latency-constrained wireless FL. The energy-efficient radio resource management strategy was investigated for bandwidth allocation and user scheduling in the Federated Edge Learning (FEEL) network, which can effectively reduce the sum of energy consumption of devices while providing a guarantee on learning speed [169]. The developed optimal bandwidth allocation scheme suggests allocating more bandwidth to devices with worse channel conditions or weaker computational capabilities in individual learning rounds. To consider the long-term effect of FL, the authors in [16] brought a long-term perspective to client selection and resource allocation problems, they identified the varying significance of learning rounds, and how this would affect the resource allocation to optimize learning performance for FL in wireless networks.

#### 4) MAB-BASED OPTIMIZATION FOR USER SCHEDULING AND RESOURCE ALLOCATION

The above studies investigate user scheduling scheme based on the assumption of the availability of prior information regarding the Channel State Information (CSI) and the knowledge of the available computational resources of each user. However, in practice, it is costly or even impossible to obtain this dynamic environment information, especially for a large-scale network. Hence, a more practical scenario without knowing the prior information needs to be considered, and the MAB tool with the ability to estimate the statistical information based on the trail-and-error rule has been exploited to design online scheduling schemes [170], [171], [172], [173]. The aim of the MAB problem is to determine the arm so as to maximize the total rewards obtained in sequential decisions. In [170], a MAB algorithm was proposed to estimate which users are expected to have the rich and available computational power and high throughput when designing the user selection strategy. Moreover, the proposed MAB-based client selection algorithm can perform exploration by selecting the users that are selected less often, and exploitation by selecting the users with rich resources, to achieve efficient user scheduling. The authors in [171] discussed the client selection problem in both ideal and non-ideal scenarios (ideal scenario: always has available clients, IID, and balanced dataset; non-ideal scenario: non-IID and imbalanced properties of local datasets, and dynamic availability of clients) by formulating it as a MAB problem and further proposing an Upper Confidence Bound (UCB)-based

algorithm to strike a balance between the exploration and exploitation actions. Different from [170], [171] that reduce the time consumed per round with a fixed number of training rounds, the authors in [173] used the MAB tool to reformulate the client scheduling problem, but aimed to reduce the number of training rounds and the time consumed per round simultaneously. In [172], the client selection problem was investigated aiming to achieve faster convergence by adopting the MAB algorithms to find a balance between selecting users with larger local loss (i.e., exploitation) and ensuring user diversity in selection (i.e., exploration).

#### C. OVER-THE-AIR COMPUTATION

In FL, the global model aggregation procedure consists of the transmission of local model updates from each user, followed by the computation of their weighted average at a central server. To realize efficient uplink model aggregation in FL, an analog AirComp was proposed as a communication and computation co-design approach by exploiting the additive nature of the wireless multiple access channels [161], [174]. With AirComp, the users transmit their model updates via analog signaling, i.e., without converting to discrete coded symbols which need to be decoded at the server side. Through joint user selection and beamforming design at the central server [160], the scheduled users then simultaneously transmit in the same communication link such that their signals overlap at the server. Given the perfect CSI at the users and accurate transmission timing, the signal overlapped from the devices to the server over-the-air naturally produces the arithmetic sum of the local model updates. To deal with residual channel gain and synchronization in AirComp, the authors in [175] referred to it as a misaligned AirComp and devised a sum-product maximum likelihood estimator to estimate the arithmetic sum of the transmitted symbols; the beamforming techniques were employed at the server to alleviate the destructive effects of the interference and noise terms due to the lack of CSI at the users and perfect CSI at the server [176], [177].

Towards developing more efficient AirComp schemes, a broadband analog aggregation scheme (BAA) was proposed to support the transmission of high-dimensional updates and which dramatically reduces the communication latency [178]. Additionally, the authors extended the BAA to FEEL in which transmitters are limited to Quadrature Amplitude Modulation (QAM) and designed a one-bit broadband digital aggregation scheme for the current digital wireless system by featuring digital modulation of local gradients [179]. Moreover, to address the channel noise caused by analog AirComp, the authors in [180] developed an AirComp FL algorithm by introducing pre-coding at the users and scaling at the server. In [181], an online energy-aware dynamic user scheduling policy was proposed to deal with non-IID data in FEEL by introducing data redundancy.

**TABLE 6.** Communication-efficient technologies for distributed learning.

Technology	Purpose	Benefits	Ref.
<b>Joint user scheduling and resource allocation</b>	Appropriately schedule the users for limited channel access, heterogeneity of users and data distributions	Improve the FL performance, reduce aggregation latency, reduce energy consumption	[16], [167]–[173]
<b>Over-the-air computation</b>	Analogy model aggregation without converting to discrete symbols	Reduce communication latency	[161], [174]–[181]
<b>Gradient compression</b>	Compress gradient updates before transmission	Reduce communication data size, save transmission spectrum bandwidth	[184]–[192]

#### D. GRADIENT COMPRESSION

Synchronous SGD has been widely used for distributed training to enhance the efficiency of large-scale distributed learning [182]. Although the overall computation time can be significantly reduced by adding more computational nodes and performing data parallelization, the gradient updates are still costly [183]. To efficiently scale up distributed training, it is crucial to overcome the communication barrier when deploying the bandwidth-consuming parallelizing SGD. Therefore, reducing the communication data size to save the transmission spectrum bandwidth in the wireless network has been extensively studied.

One way to reduce the size of the transmitted gradients is to quantize them to low-precision values [184], [185], [186], [187]. In [184], 1-bit SGD with error feedback was proposed for speech-scale DNNs. Quantized SGD (QSGD) was proposed by considering the trade-off between communication bandwidth and convergence time in [185]. To be specific, the proposed QSGD scheme has an adjustable number of bits sent per iteration with possibly higher variance. Similarly, the authors in [186] developed the ternary gradients. Apart from quantizing gradients, in [187], the authors also considered bit convolution kernels to accelerate both model training and inference. The other way to save the gradients data size is named as gradient sparsification [188], [189], [190], [191]. The intuitive way is to eliminate the small-amplitude gradients below a pre-defined constant threshold and only send the remaining gradients [188]. In [189], the authors proposed gradient dropping by sparsifying the gradients, and then they combined the layer normalization to keep the convergence speed. However, the pre-defined threshold is difficult to select in practice. To avoid inappropriate threshold selection, the authors in [190] proposed a method that only chooses a fixed proportion of positive and negative gradients, respectively. In [191], a more advanced technique that can automatically tune the compression rate based on local gradients activity was studied.

To greatly reduce the communication bandwidth, Deep Gradient Compression (DGC) was proposed in [192], which not only employs gradient sparsification to reduce the bandwidth but also employs some other techniques, such as local gradient accumulation, momentum correction, local gradient clipping, momentum factor masking, and warm-up

training, to guarantee the model convergence and improve learning accuracy. Recently, a joint local compression and global aggregation approach called Analog distributed SGD (A-DSGD) was proposed to further address the bandwidth limitation in wireless communications [161]. In A-DSGD, the distributed local users first sparsify their gradients based on a compression ratio and then project them to a lower-dimensional space imposed by the available channel bandwidth. These projections are sent directly over multiple access channels without employing any digital coding. This approach can significantly reduce the communication overhead and save transmission resources as multiple distributed devices can transmit compressed gradients to the center server simultaneously through the same channel.

#### E. DISCUSSION AND OUTLOOK

When deploying distributed learning in wireless networks, the transmission of model parameters is decided by the quality of the wireless communication links. This raises higher standards for classical communication technologies, and thus some novel technologies are required to improve them for providing better communication performance with higher reliability and lower time latency. Table 6 summarizes the state-of-art technologies, including user scheduling and resource allocation, over-the-air computation, and gradient compression, to assist the share of model parameters in distributed learning with better communication efficiency. User scheduling and resource allocation is a good approach to deal with limited spectrum resources and diverse users with the goal of optimizing the convergence performance of distributed learning, but the complexity of the user scheduling scheme itself may affect the convergence time and needs to be minimized.

Apart from optimizing resource allocation and scheduling schemes for efficient communications, AirComp is a promising technique that backtracks analog communications for direct model aggregation without digital converting. Furthermore, reducing the size of local model updates at the information source before the transmission is another efficient technique that can not only save the spectrum bandwidth but also reduce the transmission latency. However, most of the aforementioned techniques are mainly studied separately, it is an inevitable trend to find an effective

way to conceive the synergistic architecture among these technologies.

## VI. AI-EMPOWERED WIRELESS COMMUNICATIONS

In Sections III and IV, wireless networks with edge computing are able to provide native AI services by leveraging RL techniques to enable intelligent decision-making and optimal network management and implementing distributed learning architecture to exploit the distributed computational resources of the local and edge devices. Due to the emerging AI applications deployed at the network edge, the requirements of communication such as near-instant millisecond latency, massive connectivity, and ubiquitous coverage have become urgently desired [193]. To meet these demands, promising technologies, such as millimeter Wave (mmWave) [194], massive MIMO [195], NOMA, and Intelligent Reflection Surfaces (IRSs) [196] have been proposed to improve communication performance. However, it is still challenging to apply conventional communication theories directly to complex application scenarios. The recent advances in AI techniques have enabled training ML models to predict the different modules in the block structure-based communication systems (i.e., modulation scheme, channel condition, transmitted signal, etc). Moreover, AI-enabled end-to-end communication can improve communication performance by assuring low communication latency. In this section, we will discuss about the DL for physical layer wireless communications techniques.

### A. THE POTENTIALS OF DL FOR WIRELESS COMMUNICATIONS

The differences between conventional wireless communications and DL-based wireless communications can be summarized from different aspects, i.e., mathematical model, design approach, assumptions, and so on. To be specific, in conventional wireless communications, the wireless transmission relies on accurate (but often simplified) mathematical models, such as the Additive White Gaussian Noise (AWGN) channel model, to design channel estimation algorithms or channel feedback schemes. However, DL usually does not rely on such mathematical models of its tasks and is particularly beneficial in the absence of accurate mathematical models. Additionally, traditional wireless transmission designs each communication system module separately using mathematical derivations, whereas DL typically trains the DNN's entire set of parameters. Besides, traditional wireless transmission often relies on idealized and simplified assumptions in its mathematical model, while DL may have an excessive number of parameters, and different neural networks have to be trained for different tasks or applications [197].

To meet the demands of the large data stream and high-speed processing in emerging complex environments, there are some challenges that need to be tackled in wireless communications [198]: complex channel modeling, local optimal

in the block structure of the communication system, and efficient computation.

### 1) DL SOLUTIONS IN WIRELESS COMMUNICATIONS

There are mainly three aspects potentials of DL that motivate researchers to find intelligent solutions for the aforementioned limitations:

- *Model-driven DL channel modeling:* Conventionally, the communication system heavily relies on mathematical models to characterize the dynamic wireless environment. However, in the real world, the environment can be very difficult to be modeled. Especially, complex scenarios with unknown or unpredictable effects are not possible to be characterized or expressed by using mathematical models. Hence, DL is introduced to address this impossibility, which can act as a black box to replace the conventional mathematical model. Moreover, by combining it with domain knowledge, model-driven DL can assist complex modeling [199].
- *Replace the block structure:* The traditional communication structure consists of multiple blocks, such as encoding, decoding, modulation, demodulation, and detection blocks, as shown in Fig. 17. Conventionally, researchers focus on optimizing specific blocks for different purposes and combining them to achieve global optimal performance through the entire system. However, this is not always guaranteed with such a simple combination of locally optimized blocks. Therefore, DL has been exploited to obtain the global optimization of the entire end-to-end communication system by replacing the separated optimization of each block [18].
- *Parallel efficient processing:* With the emergence of resource-constrained wireless devices, a large amount of data exchange causes huge computational costs. It is even more challenging for real-time data processing in a complex environment with advanced technologies. One of the convincing reasons to apply DL to deal with such concern is that the trained DL methods can pass through parallel distributed memory architectures, such as the graphic processing units and specialized computation chips that can demonstrate fast and energy-efficient computational ability [200].

### 2) PARTIAL AND COMPLETE ALGORITHM REPLACEMENT

The implementation of DL in a physical layer can be categorized into partial algorithm replacement and complete algorithm replacement [201]. For partial algorithm replacement, inspired by the idea that unfolds the inference iterations as layers in a deep network [202], part of the existing algorithm can be replaced by the neural network layers. For example, [203] considered the application of neural network architecture for sparse linear inversion in compressive sensing to assist in recovering the sparse signal from the noisy measurements. Differently, for complete algorithm replacement, the DL algorithms can be treated as black boxes

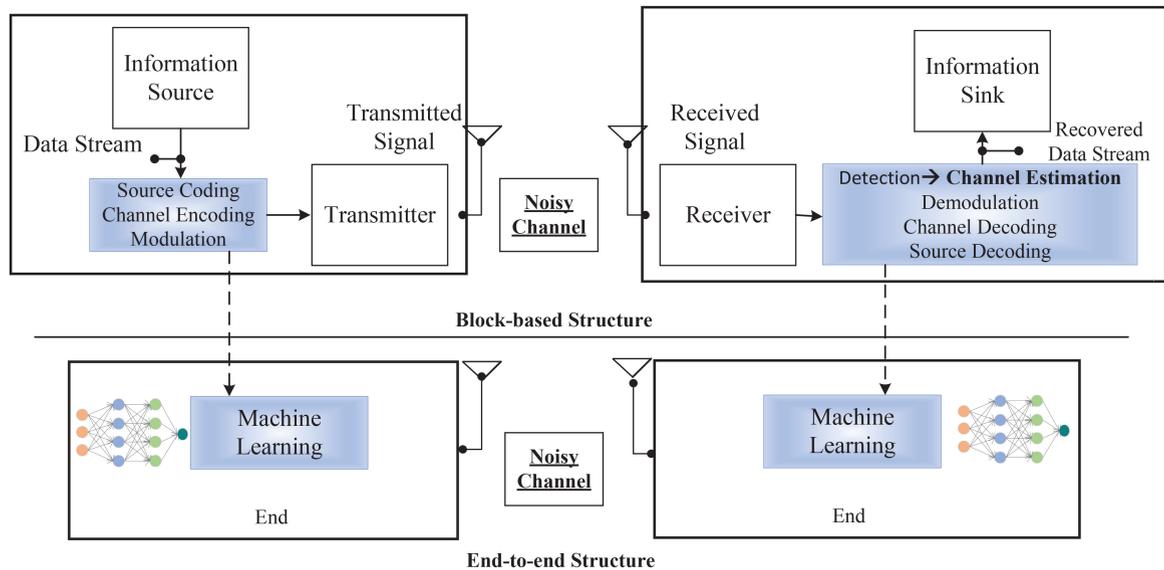


FIGURE 17. The block diagram of conventional communications block and the end-to-end structure.

that can be trained and applied for multiple purposes in the communication systems.

### B. FROM BLOCK-BASED TO END-TO-END STRUCTURE

Conventionally, the communication systems are designed based on separate signal processing blocks (i.e., source coding, channel coding, and so on) that can be constructed as a chain structure with separate sub-optimal performance. In recent years, with the DL algorithms evolving, the end-to-end system that can utilize the advantages of DL for global optimization has been further investigated. In this subsection, the evolution of the communication structure will be discussed.

#### 1) DL IN BLOCK-BASED COMMUNICATIONS STRUCTURE

As shown in Fig. 17, a typical wireless communication system can be summarized as a chain diagram with multiple independent blocks as the block-based structure. Each block plays a vital role in executing an independent task, for example, source coding, channel encoding, modulation, channel estimation, demodulation, channel decoding, and source decoding.

- *Signal compression:* In physical layer communications, downlink CSI feedback is one of the determinants to achieve performance gain at the BS. However, the practical challenge is that a large number of antenna elements leads to excessive transmission overhead. Although the sparse spatial and temporal correlations of the CSI have been studied to reduce the heavy feedback overhead, the sparse structure is not practically guaranteed. In [204], the authors proposed a CsiNet as an encoder to compress feedback and reconstruct the CSI. Specifically, the compression task is done at the user side by inputting the angular-delay domain channel matrix to a CNN layer. Then two feature maps

at the output are vectorized as real-valued compressed information for feedback.

- *Modulation classification:* Automatic modulation recognition has been studied for many decades. In [205], the neural network architecture has been designed as the modulation classifier after the feature extraction step to distinguish signals from both digital and analog modulation schemes. To omit the feature extraction step, the automatic learning CNN-based method is proposed in [20] to learn the modulation schemes directly from time-sequence raw data in the radio domain.
- *Channel decoding:* The fundamental purpose of channel coding and channel decoding is to detect and correct errors in the noisy channels. In [206], the authors proposed the special structure, DNN-based belief propagation algorithm, which contains odd hidden layers that transmit output from variable nodes to check nodes and even layers transmit output from check nodes to variable nodes. Through such a structure, the performance of decoding high-density parity-check codes can be improved. Alternatively, the authors in [207] proposed a plain DNN structure-based decoder, named neural network decoder, to achieve a competitive result and high-level parallelization.
- *Signal detection:* With the increasingly complex applications emerging in communication systems, information detection becomes harder due to the complex time-varying channel model. DL-based detectors have been designed in [18], [208]. However, in [208], the authors only considered the received signal and channel matrix as inputs to reconstruct the transmitted signal. In [18], the authors treated the channel as a black box and designed a five-layer fully connected DNN for Orthogonal Frequency-Division Multiplexing (OFDM) signal detection.

## 2) DL FOR END-TO-END COMMUNICATIONS

The structure of the end-to-end communication system can be found in the lower part of Fig. 17. All of the individual blocks at the transmitter (receiver) side are treated as a whole which is called the transmitter (receiver) end. Particularly, this structure can take the advantage of data-driven DL, as both transmitter and receiver ends can learn to automatically encode and decode source data. The DL model embedded at both ends is optimized by minimizing the loss function which consists of the difference between the true value and the estimation value. Compared to independent block optimization in block-based communications, end-to-end optimization can guarantee a global solution [209]. In [210], the DL-based auto-encoder end-to-end communication system in MIMO channels for both closed-loop and open-loop systems was proposed. Specifically, closed-loop and open-loop are distinguished by whether to consider a CSI feedback system. However, these end-to-end model training mechanisms incur a practical problem, and the back-propagation stage during model training has to pass through the unknown wireless channel. Hence, more practically, the authors in [211] separately designed a DNN-based transmitter and a DNN-based receiver. Explicitly, the transmitter that is robust to various channel conditions learns to transform the input data. Apart from this, the receiver consists of two respective DNN modules used for channel information extraction and data recovery.

For robust DL model training, the process can be done in advance and can be trained by exploiting the near-infinite computation and storage resources in the cloud server based on different tasks or application purposes. For more timely training, the training process can be done at the edge server that is placed near the end device for more frequent model updates. Similar to the cloud server, the edge server also has more powerful computation and storage ability than end devices. Apart from utilizing these computation and memory capacities for DL algorithms training at the servers, it is proved that the communication overhead can be greatly reduced in DL-based end-to-end wireless communication systems. In other words, the pilot-free paradigm can be realized in this end-to-end system [211].

### C. DL FOR WIRELESS COMMUNICATIONS TECHNOLOGIES

In the past decade, with the explosive demands of wireless communications wireless technologies such as mmWave, massive MIMO, NOMA, and IRS have been developed to improve communication performance from spatial-efficiency, spectral-efficiency, and energy-efficiency perspectives. However, with the advanced technologies implemented in the communication systems, it is even challenging to acquire precise complex mathematical models to realize robust communications. Therefore, DL is a reliable candidate to support practical implementations of the aforementioned advanced technologies. In this subsection, the works focused

on DL-based frameworks in advanced technology-assisted wireless communications will be introduced.

## 1) DL FOR MMWAVE MASSIVE MIMO SYSTEM

MmWave band has been recognized as the spectrum that can bring magnitude improvement of speed and capacity for future wireless communications. To mitigate the poor diffraction ability of mmWave, it is widely studied to implement massive MIMO in mmWave systems and apply hybrid precoding techniques to achieve multiplex data streams, thus enhancing the system throughput. Although compressive sensing-related algorithms have been broadly deployed to reduce the computation complexity caused by the massive number of antenna elements in the mmWave massive MIMO systems for precoding design, the inadequate leverage of the structural characteristics of mmWave systems brings the urgent need of developing more advanced methods. Therefore, a DL-based mmWave massive MIMO framework for effective hybrid precoding design has been proposed [212]. Specifically, the selection of the optimized hybrid precoders is designed as the mapping relationship in the DNN. Similarly, [213] explored the DNN-based beam training schemes to deal with the nonlinear and nonmonotonic properties of channel power leakage in mmWave.

## 2) DL FOR NOMA SCHEME

Apart from exploring under-utilized spectrum in the ultra-high-frequency bands (i.e., mmWave), as the spectral efficient technology that enables each user to operate in the same frequency band at the same time through assigning different power levels, NOMA has also drawn significant attention. Conventional methods for sum data rate and reliability optimization in NOMA systems require high computation complexity to solve the nonlinear optimization power allocation problems with known channel state information. However, in practice, acquiring fast time-varying channel information is very challenging. Conventional methods are not efficient and reliable enough to capture complicated channel characteristics. To overcome such difficulty, a DL-aided NOMA system has been proposed in [214]. To be specific, an LSTM network has been established to detect the channel information automatically through offline training and online learning process.

## 3) DL FOR IRS-ASSISTED SYSTEM

With the flexible feature that can control and reflect the electromagnetic signal by changing the phase of the impinging signals, IRSs have been recognized as a promising technique to broadening the communication coverage for future wireless communication systems. Although the implementation of the IRSs with almost-passive elements is inexpensive, challenges have been raised at the receiver in estimating the CSI and the signal phase angles. Reference [215] modeled the IRS-assisted communication systems as the end-to-end systems through the auto-encoder DL technique. Explicitly,

**TABLE 7.** DL for wireless communications from block-based to end-to-end structure.

DL in block-based structure				DL in end-to-end structure			
Block	Purpose	DL Algorithm	Ref.	System	Purpose	DL Algorithm	Ref.
Source encoder	Signal compression	CNN	[204]	MIMO	Transceiver design	DNN	[210], [211]
Modulation	Modulation classification	NN,CNN	[20], [205]	mmWave massive MIMO	Precoder design	DNN	[212], [213]
Channel decoder	Channel decoding	DNN	[206], [207]	NOMA	Channel estimation	LSTM	[214]
Source decoder	Signal detection	DNN	[18], [208]	IRS	Symbol recovery, channel tracking	DNN, LSTM	[215], [216]

the cascaded channels, which are the channels reflected from IRSs, have been designed as a DNN that can reduce the environmental impairments effect. Moreover, [216] proposed an LSTM-based algorithm to track the constantly changing CSI in an IRS-assisted UAV communication networks.

#### D. DISCUSSION AND OUTLOOK

The conventional signal processing algorithms with tractable information theory mathematical models have become unable to model the imperfection and non-linearity of the complex and time-varying wireless communication systems. Therefore, the model-free characteristic of the DL algorithm motivates researchers to deploy it in physical layer communications. Table 7 summarizes the aforementioned research works that focus on implementing DL algorithms for different purposes in wireless communication systems from block-based to end-to-end structures. When applying DL algorithms in the block-based structure, it only can provide a local sub-optimal in each individual block (i.e., source encoder, modulation, and so on), while the global optimal can be achieved when applying it in an end-to-end structure.

Therefore, with the development of more advanced communication technologies such as MIMO, mmWave massive MIMO, NOMA, and IRS, DL has been widely studied and deployed in end-to-end communications. As the fundamental support for model updates transmission in distributed learning, wireless communications are expected to evolve with the combination of these advanced technologies for superior performance. Additionally, with the time-series property of the dynamic environment, LSTM which can extract the time relationships has drawn increasing attention to be applied in the physical layer. Besides, since the wireless environment is typically fluctuating, it is necessary for DL-based wireless systems to repeatedly retrain from scratch in order to maintain performance over time, which takes time and is computationally expensive. Therefore, DL-based approaches must be reliable and adaptable in some previously undiscovered scenarios, and new learning algorithms need to be developed (e.g., transfer learning). Most of the above studies

train the DL model through supervised learning (i.e., with labeled data); however, it is not practical in the real world to obtain the accurately labeled data in advance for model training. Therefore, it is necessary to design the dynamic loss function for unsupervised learning to maintain solid performance for both DL model training and execution in the physical layer of wireless communications.

#### VII. CHALLENGES AND FUTURE OPPORTUNITIES

It is envisioned that 6G wireless networks are urgently needed to support applications beyond current mobile use scenarios, such as virtual and augmented reality (VR/AR), ubiquitous instant communications, and pervasive intelligence, so that native AI architecture with its distributed characteristics and the pervasive use of AI techniques could provide potential support for those applications. To provide native AI support, edge computing, and end-to-end architecture were investigated to embrace intelligence at everywhere in the network system [3], [217]. However, the existing research only makes the fundamental step of native AI wireless networks. There are still many challenges that need thoughtful exploration. In this section, we outline the challenges and future opportunities separately related to each topic we discussed above.

##### A. DISTRIBUTED COMPUTATION OFFLOADING

Researchers are now moving the focus to design efficient offloading schemes and resource allocation methods for more practical multi-user computation offloading problems. The multi-agent RL framework has drawn significant attention from academia to model the multi-user computation offloading problem, and a few approaches, including independent learning, information sharing, conjecture-based and prediction-based algorithms, have been proposed to address the formulated multi-agent computation offloading problem. Specifically, the conjecture-based and prediction-based algorithms addressed the non-stationary issue in independent learning and large communication overhead in information-sharing algorithms and became potential solutions to the

multi-agent problem. However, the conjecture-based algorithm needs the training data collected from online interactions with the network elements, which slows down the training process. The potential solution is to develop off-policy learning algorithms that utilize the pre-collected online interaction data for offline training. Another approach is the prediction-based algorithm that exploits the LSTM to predict the global state with the past side information, but this approach relies on centralized offline training and that is challenging when supporting large-scale networks.

## B. CUSTOMIZED DISTRIBUTED LEARNING

Most existing works have studied distributed learning to enable training the traditional ML models in a distributed manner. However, due to the increasing user-centric applications and the heterogeneity of the local dataset and wireless environment, it is necessary to ensure that the learned model can capture users' individual characteristics. Thus, designing the customized distributed learning model is an inevitable direction in wireless networks.

### 1) FROM ZERO-SHOT LEARNING TO META-LEARNING

Recently, multiple learning schemes, such as zero-shot, one-shot, few-shot, and meta-learning, have been designed based on personalized fewer sample datasets to train the ML models and save the wireless communication resources [218], [219], [220], [221]. In [218], the authors proposed a learning framework called zero-shot learning which firstly distinguished the features of the input without any learning and then trained the ML model based on these features. Similarly, the authors in [219] proposed one-shot federated learning which firstly distills the client's private dataset and sends the synthetic data to the server to train the global model. Moreover, the few-shot learning framework refers to learning from a few labeled datasets [220]. As one of the special categories of few-shot learning, meta-learning attempts to reduce human intervention and let the system learn by itself [221]. As the aforementioned learning frameworks can be customized to certain applications and save communication resources at the same time, it is worthy to extend these learning schemes to the applications in the distributed wireless network that have limited communication resources [222].

### 2) PERSONALIZED DISTRIBUTED LEARNING

The primary purpose of involving distributed users in distributed learning is that a global model can be trained by benefiting from the collaborative training of these users and their decentralized computational resources. However, the heterogeneity of the users, including user heterogeneity (e.g., diverse storage hardware, computational capacities, network conditions, battery power) [223], data heterogeneity (e.g., non-IID and imbalanced data distribution), and model heterogeneity (e.g., hetero-modal data), will affect the convergence performance of the model training. For instance, when the users have sufficient personalized data, joining the global

model training can hurt the model's ability for personalization. With non-IID data, the local model updates of each user are of different significance to the global model training [224]. Moreover, distributed learning with hetero-modal data is challenging, thus the multi-model fusion of RF and image data is considered to train a global model for received power prediction in mmWave networks [225]. Therefore, personalized distributed learning taking into account the diversity of users and the hetero-modal data is a practical issue and full of challenges.

## C. CONTRIBUTION-DEPENDENT INCENTIVE MECHANISMS

Designing proper incentive mechanisms for active participants in distributed learning is an emerging research topic, since clients that hold useful data sources may not want to actively provide local updates without rewards. To design an optimal incentive mechanism that can motivate clients to participate in distributed learning, there are some key characteristics, such as information unsharing and contribution evaluation, that can be considered as the metrics to develop incentive decisions for users [102]. However, it becomes more challenging if taking the uncertainty of the dynamic conditions into consideration (e.g., the unpredictable decisions of the participants, unfixed training periods, time-varying data sources, diverse data quality caused by the communication environment, and so on).

## D. ASYNCHRONOUS DISTRIBUTED LEARNING

Most of the existing works focus on synchronous federated learning assuming synchronous model aggregation, but it is not practical since the users do not always complete local gradient calculation and model parameters transmission at the same time due to the heterogeneity of devices and their individual datasets. Asynchronous federated learning has been studied intensively to address this challenge using dynamic learning rates, weight aggregation, and a regularized loss function for local users. However, fully asynchronous federated learning with sequential updating can face the problem of high communication costs caused by frequent model updating and transmission of local updates. A few approaches, such as cluster FL and periodic model aggregation, have been proposed to tackle those concerns by managing the update frequency of the local users. Thus, a trade-off between convergence performance and communication costs needs to be carefully considered by designing proper update strategies.

The existing strategies, such as user selection, weight aggregation, and cluster FL, are effective to improve convergence performance for asynchronous federated learning with heterogeneous users. However, different performance improvement strategies are suitable for different application scenarios. For example, a semi-asynchronous FL with suitable weighted aggregation strategies could be an optimal solution to the scenario when the disparity in computing capabilities among heterogeneous devices is extremely high.

Hence, several performance improvement strategies could be developed together to improve the efficiency of asynchronous federated learning, but this could result in a decline in efficiency to a certain extent. In [16], the authors pointed out a potential research direction on the comprehensive analysis of the balance between multiple performance improvement strategies and time consumption.

When considering asynchronous learning in the hybrid distributed learning architectures discussed in Section IV, asynchronous distributed learning needs to be redesigned to adapt to the specific learning architecture to improve learning performance. For instance, with the hybrid learning architecture, the clustering approach can be used to group the users into different clusters according to the learning method they choose, and then weighted aggregation could be used to aggregate updates from different clusters in an asynchronous way.

### E. COMMUNICATION EFFICIENCY FOR DISTRIBUTED LEARNING

In distributed learning, the communications between the central server and the local users constantly exchange information during the training stage, which consumes a huge amount of communication resources. To improve network efficiency, communication-efficient technologies, including AirComp and gradient compression, have been proposed but each of them still faces some challenges. Moreover, assisted wireless technologies, such as IRS, could also be a potential option to improve communication performance for distributed learning.

#### 1) GRADIENT COMPRESSION AND OVER-THE-AIR COMPUTATION

Gradient compression and AirComp are two main technologies that have been exploited to save communication resources for deploying FL in wireless communications. With gradient compression, although the quantification [184], [185], [186], [187] and sparsification [188], [189], [190], [191] were studied and could achieve solid compression performance, some useful gradient information can still be lost. Hence, a specific gradient compression method should be designed in certain learning models for various wireless applications that can tolerate some degree of information loss. In AirComp, analog-based transmission is designed, which allows the weighted aggregation to be obtained directly over the air without aggregating individual parameters acquired from distributed users. However, if a large number of users participating in training, it is more challenging to realize reliable aggregation using the wireless multiple access channel in the complex systems [160]. Therefore, it is essential to design effective approaches that can mitigate channel distortion in the network and interference among users to provide a robust and efficient transmission that can support AirComp. Moreover, collectively considering appropriate gradient compression and dependable over-the-air aggregation to stack the

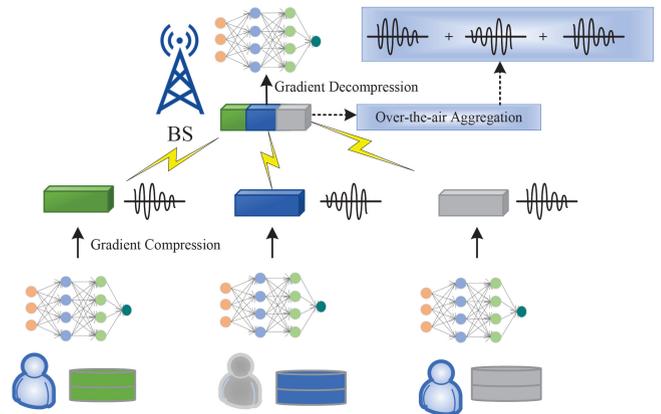


FIGURE 18. The architecture of joint gradient compression and over-the-air aggregation.

communication benefits can be another promising research direction. As shown in Fig. 18, the architecture of joint gradient compression and AirComp aggregation is presented.

#### 2) IRS-ASSISTED DISTRIBUTED LEARNING

Due to the vulnerability of mmWave transmission, IRS is an emerging low-cost technology that can reconfigure the wireless propagation directions to improve both spectrum and energy efficiencies in wireless networks. Particularly, the phase shifts of the signal can be adjusted through a large amount of passive reflecting elements to steer the signal in specific directions. Hence, IRS can be leveraged to enhance the received signal strength and this is beneficial to both gradient transmission and AirComp [226], [227]. However, jointly designing the aggregation beamformers at the BS and the phase shifts at the IRS can be a very challenging task.

### F. PRIVACY AND SECURITY

Although distributed learning is capable of preventing direct raw data leakage from the local devices, private information can still be extracted through intercepted gradient updates that are exchanged between the distributed devices and the central server. Moreover, during the gradient transmission, attacks and data poisoning can also threaten the security of the distributed system [228].

#### 1) PRIVACY LEAKAGE PROTECTION

Distorting [229] and dummy [230] are two techniques that can protect data privacy from the user side. In [229], the authors proposed the randomized mechanism that consists of random sub-sampling and distorting steps to approximate the average and hide the individual client's contributions. However, the trade-off between privacy-preserving and model convergence performance should be further studied. In [230], the authors designed a method that transmits the original information together with probabilistically dummy packets. Since dummy parameters are sent as redundancy, extra communication resources, such as bandwidth and transmission energy, are required. The encryption-based technique

to prevent data inspection at the central server side was proposed [231]. However, additional overhead is needed for encryption in this case. Therefore, for privacy protection, it is essential to find the balance between privacy, model performance, and communication efficiency, at both clients and central server sides.

## 2) ANOMALY DETECTION

When training the distributed learning model, the model parameters are transmitted through the wireless network. However, abnormal data samples can greatly influence the overall model training. Anomaly detection which can distinguish abnormal data can not only be used to detect data poisoning and attacks from adversaries [232] but also can monitor the abnormal operations in the wireless network, such as traffic load, computation resources usage, etc. Therefore, embedding anomaly detection into appropriate distributed learning techniques can provide extensive contributions to both secure model updating and system inspection.

## VIII. CONCLUSION

In this article, the recent literature on distributed intelligence in wireless networks has been surveyed with an emphasis on the following aspects: the new concept of native AI networks, distributed learning architectures for heterogeneous networks, RL techniques assisted edge computing, communication-efficient technologies for distributed learning, as well as DL-enabled end-to-end communication structure and DL-assisted advanced communication technologies. Specifically, we highlighted the comparisons of different ML algorithms-enabled edge computing in Section III and the advantages of different distributed learning architectures in Section IV. Investigating ML-assisted communication technologies and structures are particularly important since they can provide more reliable and ultra-low latency communication performance. It is worth pointing out that when designing efficient communication technologies, the convergence-based metrics are proposed to investigate user scheduling and resource allocation, and the special technology with direct ML model aggregation, namely over-the-air computation, is also presented in Section V. Finally, the challenges of existing research works on distributed intelligence in wireless networks have been identified, and also the future opportunities were discussed.

## REFERENCES

- [1] J. Hoydis, F. A. Aoudia, A. Valcarce, and H. Viswanathan, "Toward a 6G AI-native air interface," *IEEE Commun. Mag.*, vol. 59, no. 5, pp. 76–81, May 2021.
- [2] K. B. Letaief, W. Chen, Y. Shi, J. Zhang, and Y.-J. A. Zhang, "The roadmap to 6G: AI empowered wireless networks," *IEEE Commun. Mag.*, vol. 57, no. 8, pp. 84–90, Aug. 2019.
- [3] J. Wu et al., "Toward native artificial intelligence in 6G networks: System design, architectures, and paradigms," Mar. 2021, *arXiv:2103.02823*.
- [4] K. L. Lueth, *State of the IoT 2020: 12 Billion IoT Connections, Surpassing Non-IoT for the First Time*, IoT Anal., Hamburg, Germany, Nov. 2020.
- [5] "Mobile statistics report, 2021–2025," Apr. 2021. [Online]. Available: [https://www.radicati.com/wp/wp-content/uploads/2021/Mobile\\_Statistics\\_Report\\_2021-2025\\_Executive\\_Summary.pdf](https://www.radicati.com/wp/wp-content/uploads/2021/Mobile_Statistics_Report_2021-2025_Executive_Summary.pdf)
- [6] "The future of the Drone economy," Levitate Capital. Dec. 2020. [Online]. Available: <https://levitatecap.com/levitate/wp-content/uploads/2020/12/White-Paper-v4.pdf>
- [7] P. Mach and Z. Becvar, "Mobile edge computing: A survey on architecture and computation offloading," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 3, pp. 1628–1656, 3rd Quart., 2017.
- [8] T. Taleb, K. Samdanis, B. Mada, H. Flinck, S. Dutta, and D. Sabella, "On multi-access edge computing: A survey of the emerging 5G network edge cloud architecture and orchestration," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 3, pp. 1657–1681, 3rd Quart., 2017.
- [9] J. Verbracken, M. Wolting, J. Katzy, J. Kloppenburg, T. Verbelen, and J. S. Rellermeyer, "A survey on distributed machine learning," *ACM Comput. Surv.*, vol. 53, no. 2, p. 30, Mar. 2020. [Online]. Available: <https://doi.org/10.1145/3377454>
- [10] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. Y. Arcas, "Applied federated learning: Improving Google keyboard query suggestions," in *Proc. Artif. Intell. Stat.*, Apr. 2017, pp. 1273–1282.
- [11] A. M. Elbir, S. Coleri, and K. V. Mishra, "Hybrid federated and centralized learning," in *Proc. 29th Eur. Signal Process. Conf. (EUSIPCO)*, Aug. 2021, pp. 1541–1545.
- [12] X. Liu, Y. Deng, and T. Mohammoodi, "A novel hybrid split and federated learning architecture in wireless UAV networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, 2022, pp. 1–6.
- [13] X. Liu, Y. Deng, and T. Mohammoodi, "Energy efficient user scheduling for hybrid split and federated learning in wireless UAV networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, 2022, pp. 1–6.
- [14] Y. Zhan, J. Zhang, Z. Hong, L. Wu, P. Li, and S. Guo, "A survey of incentive mechanism design for federated learning," *IEEE Trans. Emerg. Topics Comput.*, vol. 10, no. 2, pp. 1035–1044, Apr.–Jun. 2022.
- [15] H.-S. Lee and J.-W. Lee, "Adaptive transmission scheduling in wireless networks for asynchronous federated learning," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 12, pp. 3673–3687, Dec. 2021.
- [16] J. Xu and H. Wang, "Client selection and bandwidth allocation in wireless federated learning networks: A long-term perspective," *IEEE Trans. Wireless Commun.*, vol. 20, no. 2, pp. 1188–1200, Feb. 2021.
- [17] N. Kato, B. Mao, F. Tang, Y. Kawamoto, and J. Liu, "Ten challenges in advancing machine learning technologies toward 6G," *IEEE Wireless Commun.*, vol. 27, no. 3, pp. 96–103, Jun. 2020.
- [18] H. Ye, G. Y. Li, and B.-H. Juang, "Power of deep learning for channel estimation and signal detection in OFDM systems," *IEEE Wireless Commun. Lett.*, vol. 7, no. 1, pp. 114–117, Feb. 2018.
- [19] C. Wang, D. Deng, L. Xu, W. Wang, and F. Gao, "Joint interference alignment and power control for dense networks via deep reinforcement learning," *IEEE Wireless Commun. Lett.*, vol. 10, no. 5, pp. 966–970, May 2021.
- [20] T. J. O'Shea, T. Roy, and T. C. Clancy, "Over-the-air deep learning based radio signal classification," *IEEE J. Sel. Topics Signal Process.*, vol. 12, no. 1, pp. 168–179, Feb. 2018.
- [21] L. Zhang, S. Lambotharan, G. Zheng, B. AsSadhan, and F. Roli, "Countermeasures against adversarial examples in radio signal classification," *IEEE Wireless Commun. Lett.*, vol. 10, no. 8, pp. 1830–1834, Aug. 2021.
- [22] D. Liu, H. Kong, X. Luo, W. Liu, and R. Subramaniam, "Bringing AI to edge: From deep learning's perspective," *Neurocomputing*, vol. 485, pp. 297–320, May 2021.
- [23] M. S. Murrshed, C. Murphy, D. Hou, N. Khan, G. Ananthanarayanan, and F. Hussain, "Machine learning at the network edge: A survey," *ACM Comput. Surveys*, vol. 54, no. 8, pp. 1–37, 2022.
- [24] J. Liu et al., "From distributed machine learning to federated learning: A survey," *Knowl. Inf. Syst.*, vol. 64, pp. 885–917, Mar. 2022.
- [25] W. Y. B. Lim et al., "Federated learning in mobile edge networks: A comprehensive survey," *IEEE Commun. Surveys Tuts.*, vol. 22, no. 3, pp. 2031–2063, 3rd Quart., 2020.
- [26] Y. Liu, X. Yuan, Z. Xiong, J. Kang, X. Wang, and D. Niyato, "Federated learning for 6G communications: Challenges, methods, and future directions," *China Commun.*, vol. 17, no. 9, pp. 105–118, Sep. 2020.

- [27] Z. Qin, G. Y. Li, and H. Ye, "Federated learning and wireless communications," *IEEE Wireless Commun.*, vol. 28, no. 5, pp. 134–140, Oct. 2021.
- [28] S. Hu, X. Chen, W. Ni, E. Hossain, and X. Wang, "Distributed machine learning for wireless communication networks: Techniques, architectures, and applications," *IEEE Commun. Surveys Tuts.*, vol. 23, no. 3, pp. 1458–1493, 3rd Quart., 2021.
- [29] J. Park et al., "Communication-efficient and distributed learning over wireless networks: Principles and applications," *Proc. IEEE*, vol. 109, no. 5, pp. 796–819, May 2021.
- [30] M. Chen et al., "Distributed learning in wireless networks: Recent progress and future challenges," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 12, pp. 3579–3605, Dec. 2021.
- [31] J. Chen and X. Ran, "Deep learning with edge computing: A review," *Proc. IEEE*, vol. 107, no. 8, pp. 1655–1674, Aug. 2019.
- [32] D. Xu et al., "Edge intelligence: Architectures, challenges, and applications," Mar. 2020, *arXiv:2003.12172*.
- [33] "Mobile future of extended reality." Qualcomm. Nov. 2020. [Online]. Available: <https://www.qualcomm.com/media/documents/files-mobile-future-of-extended-reality-xr.pdf>
- [34] P. McDonald. "Google developer Blog." Apr. 2008. [Online]. Available: <http://googleappengine.blogspot.com/2008/04/introducing-google-app-engine-our-new.html>
- [35] M. Satyanarayanan, V. Bahl, R. Caceres, and N. Davies, "The case for VM-based cloudlets in mobile computing," *IEEE Pervasive Comput.*, vol. 8, no. 4, pp. 14–23, Oct.–Dec. 2009.
- [36] Y. C. Hu, M. Patel, D. Sabella, N. Sprecher, and V. Young, "Mobile edge computing—A key technology towards 5G," ETSI, Sophia Antipolis, France, White Paper, Sep. 2015.
- [37] A. Filali, A. Abouaomar, S. Cherkaoui, A. Kobbane, and M. Guizani, "Multi-access edge computing: A survey," *IEEE Access*, vol. 8, pp. 197017–197046, 2020.
- [38] A. C. Baktir, A. Ozgovde, and C. Ersoy, "How can edge computing benefit from software-defined networking: A survey, use cases, and future directions," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 4, pp. 2359–2391, 4th Quart., 2017.
- [39] A. A. Abdellatif, A. Mohamed, C. F. Chiasserini, M. Tlili, and A. Erbad, "Edge computing for smart health: Context-aware approaches, opportunities, and challenges," *IEEE Netw.*, vol. 33, no. 3, pp. 196–203, May/June. 2019.
- [40] Y. Siriwardhana, P. Porambage, M. Liyanage, and M. Ylianttila, "A survey on mobile augmented reality with 5G mobile edge computing: Architectures, applications, and technical aspects," *IEEE Commun. Surveys Tuts.*, vol. 23, no. 2, pp. 1160–1192, 2nd Quart., 2021.
- [41] Y. Li, L. Sun, and W. Wang, "Exploring device-to-device communication for mobile cloud computing," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2014, pp. 2239–2244.
- [42] X. Tao, K. Ota, M. Dong, H. Qi, and K. Li, "Performance guaranteed computation offloading for mobile-edge cloud computing," *IEEE Wireless Commun. Lett.*, vol. 6, no. 6, pp. 774–777, Dec. 2017.
- [43] *Key Marketing Trends for 2017 and Ideas for Exceeding Customer Expectations*, IBM Marketing Cloud, Armonk, NY, USA, 2017.
- [44] V. Andalibi, J. Dev, D. Kim, E. Lear, and L. J. Camp, "Making access control easy in IoT," in *Proc. Int. Symp. Human Aspects Inf. Security Assurance*, Jul. 2021, pp. 127–137.
- [45] S. Sardellitti, G. Scutari, and S. Barbarossa, "Joint optimization of radio and computational resources for multicell mobile-edge computing," *IEEE Trans. Signal Inf. Process. Netw.*, vol. 1, no. 2, pp. 89–103, Jun. 2015.
- [46] C. You, K. Huang, H. Chae, and B.-H. Kim, "Energy-efficient resource allocation for mobile-edge computation offloading," *IEEE Trans. Wireless Commun.*, vol. 16, no. 3, pp. 1397–1411, Mar. 2017.
- [47] M. Chen and Y. Hao, "Task offloading for mobile edge computing in software defined ultra-dense network," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 3, pp. 587–597, Mar. 2018.
- [48] T. X. Tran and D. Pompili, "Joint task offloading and resource allocation for multi-server mobile-edge computing networks," *IEEE Trans. Veh. Technol.*, vol. 68, no. 1, pp. 856–868, Jan. 2019.
- [49] Y. Mao, J. Zhang, and K. B. Letaief, "Dynamic computation offloading for mobile-edge computing with energy harvesting devices," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 12, pp. 3590–3605, Dec. 2016.
- [50] Y. Mao, J. Zhang, S. H. Song, and K. B. Letaief, "Stochastic joint radio and computational resource management for multi-user mobile-edge computing systems," *IEEE Trans. Wireless Commun.*, vol. 16, no. 9, pp. 5994–6009, Sep. 2017.
- [51] J. Zhang, W. Xia, F. Yan, and L. Shen, "Joint computation offloading and resource allocation optimization in heterogeneous networks with mobile edge computing," *IEEE Access*, vol. 6, pp. 19324–19337, 2018.
- [52] Q.-V. Pham, T. Leanh, N. H. Tran, B. J. Park, and C. S. Hong, "Decentralized computation offloading and resource allocation for mobile-edge computing: A matching game approach," *IEEE Access*, vol. 6, pp. 75868–75885, 2018.
- [53] J. Li, H. Gao, T. Lv, and Y. Lu, "Deep reinforcement learning based computation offloading and resource allocation for MEC," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Apr. 2018, pp. 1–6.
- [54] X. Chen, H. Zhang, C. Wu, S. Mao, Y. Ji, and M. Bennis, "Optimized computation offloading performance in virtual edge computing systems via deep reinforcement learning," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 4005–4018, Jun. 2019.
- [55] K. Hornik, M. Stinchcombe, and H. White, "Multilayer feedforward networks are universal approximators," *Neural Netw.*, vol. 2, no. 5, pp. 359–366, Jan. 1989.
- [56] J. Schmidhuber, "Deep learning in neural Networks overview," *Neural Netw.*, vol. 61, pp. 85–117, Jan. 2015.
- [57] S. Zhang, C. Zhang, Z. You, R. Zheng, and B. Xu, "Asynchronous stochastic gradient descent for DNN training," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, May 2013, pp. 6660–6663.
- [58] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Commun. ACM*, vol. 60, no. 6, pp. 84–90, 2017.
- [59] R. C. Gonzalez, "Deep convolutional neural networks [lecture notes]," *IEEE Signal Process. Mag.*, vol. 35, no. 6, pp. 79–87, Nov. 2018.
- [60] V. Mnih et al., "Human-level control through deep reinforcement learning," *Nature*, vol. 518, no. 7540, pp. 529–533, 2015.
- [61] H. van Hasselt, A. Guez, and D. Silver, "Deep reinforcement learning with double  $Q$ -learning," in *Proc. AAAI Conf. Artif. Intell.*, Mar. 2016, pp. 1–13.
- [62] Z. Wang, T. Schaul, M. Hessel, H. van Hasselt, M. Lanctot, and N. de Freitas, "Dueling network architectures for deep reinforcement learning," in *Proc. Int. Conf. Mach. Learn.*, vol. 48, Nov. 2015, pp. 1995–2003.
- [63] D. Silver, G. Lever, N. Heess, T. Degris, D. Wierstra, and M. Riedmiller, "Deterministic policy gradient algorithms," in *Proc. 31st Int. Conf. Mach. Learn.*, vol. 32, Jan. 2014, pp. 387–395.
- [64] T. P. Lillicrap et al., "Continuous control with deep reinforcement learning," Sep. 2015, *arXiv:1509.02971*.
- [65] V. Mnih et al., "Asynchronous methods for deep reinforcement learning," in *Proc. 33rd Int. Conf. Mach. Learn.*, vol. 48, Feb. 2016, pp. 1928–1937.
- [66] J. Schulman, S. Levine, P. Moritz, M. I. Jordan, and P. Abbeel, "Trust region policy optimization," in *Proc. 32nd Int. Conf. Mach. Learn.*, vol. 37, Feb. 2015, pp. 1889–1897.
- [67] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov, "Proximal policy optimization algorithms," Jul. 2017, *arXiv:1707.06347*.
- [68] K. Zhang, Z. Yang, and T. Başar, "Multi-agent reinforcement learning: A selective overview of theories and algorithms," in *Handbook of Reinforcement Learn. Control*. Cham, Switzerland: Springer, Jun. 2021, pp. 321–384.
- [69] M. Tan, "Multi-agent reinforcement learning: Independent vs. cooperative agents," in *Proc. Mach. Learn.*, 1993, pp. 330–337.
- [70] M. L. Littman, "Markov games as a framework for multi-agent reinforcement learning," in *Proc. Mach. Learn.*, Jan. 1994, pp. 157–163.
- [71] C. Tao Chu et al., "Map-reduce for machine learning on multicore," in *Proc. Adv. Neural Inf. Process. Syst.*, Dec. 2007, pp. 1–8.
- [72] J. G. Shanahan and L. Dai, "Large scale distributed data science using Apache spark," in *Proc. 21st ACM SIGKDD Int. Conf. Knowl. Disc. Data Min.*, Aug. 2015, pp. 2323–2324.
- [73] M. Li et al., "Parameter server for distributed machine learning," in *Proc. Big Learn. NIPS Workshop*, vol. 6, Dec. 2013, p. 2.

- [74] C.-H. Hu, Z. Chen, and E. G. Larsson, "Scheduling and aggregation design for asynchronous federated learning over wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 41, no. 4, pp. 874–886, Apr. 2023.
- [75] T. Yang et al., "Applied federated learning: Improving Google keyboard query suggestions," Dec. 2018, *arXiv:1812.02903*.
- [76] O. Gupta and R. Raskar, "Distributed learning of deep neural network over multiple agents," *J. Netw. Comput. Appl.*, vol. 116, pp. 1–8, Aug. 2018.
- [77] P. Vepakomma, O. Gupta, T. Swedish, and R. Raskar, "Split learning for health: Distributed deep learning without sharing raw patient data," Dec. 2018, *arXiv:1812.00564*.
- [78] P. Vepakomma, O. Gupta, A. Dubey, and R. Raskar, "Reducing leakage in distributed deep learning for sensitive health data," May 2019, *arXiv:1812.00564*.
- [79] P. Vepakomma, T. Swedish, R. Raskar, O. Gupta, and A. Dubey, "No peek: A survey of private distributed deep learning," Dec. 2018, *arXiv:1812.03288*.
- [80] A. Singh, P. Vepakomma, O. Gupta, and R. Raskar, "Detailed comparison of communication efficiency of split learning and federated learning," Sep. 2019, *arXiv:1909.09145*.
- [81] C. Thapa, M. A. P. Chamikara, and S. Camtepe, "SplitFed: When federated learning meets split learning," Apr. 2020, *arXiv:2004.12088*.
- [82] A. M. Elbir, A. K. Papazafireopoulos, and S. Chatzinotas, "Federated learning for physical layer design," *IEEE Commun. Mag.*, vol. 59, no. 11, pp. 81–87, Nov. 2021.
- [83] J. Dean et al., "Large scale distributed deep networks," in *Proc. Adv. Neural Infor. Process. Syst.*, vol. 25, pp. 1223–1231, 2012.
- [84] C. Xie, S. Koyejo, and I. Gupta, "Asynchronous federated optimization," Mar. 2019, *arXiv:1903.03934*.
- [85] Z. Wang, Z. Zhang, and J. Wang, "Asynchronous federated learning over wireless communication networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2021, pp. 1–7.
- [86] D. Stripelis, P. M. Thompson, and J. L. Ambite, "Semi-synchronous federated learning for energy-efficient training and accelerated convergence in cross-silo settings," *ACM Trans. Intell. Syst. Technol.*, vol. 13, no. 5, p. 78, 2022.
- [87] C. Xu, Y. Qu, Y. Xiang, and L. Gao, "Asynchronous federated learning on heterogeneous devices: A survey," Sep. 2021, *arXiv:2109.04269*.
- [88] J. Hao, Y. Zhao, and J. Zhang, "Time efficient federated learning with semi-asynchronous communication," in *Proc. IEEE 26th Int. Conf. Parallel Distrib. Syst. (ICPADS)*, Dec. 2020, pp. 156–163.
- [89] Z. Wang, H. Xu, J. Liu, H. Huang, C. Qiao, and Y. Zhao, "Resource-efficient federated learning with hierarchical aggregation in edge computing," in *Proc. IEEE Conf. Comput. Commun. (INFOCOM)*, May 2021, pp. 1–10.
- [90] W. Sun, S. Lei, L. Wang, Z. Liu, and Y. Zhang, "Adaptive federated learning and digital twin for Industrial Internet of Things," *IEEE Trans. Ind. Informat.*, vol. 17, no. 8, pp. 5605–5614, Aug. 2021.
- [91] H. Yang, J. Zhao, Z. Xiong, K.-Y. Lam, S. Sun, and L. Xiao, "Privacy-preserving federated learning for UAV-enabled networks: Learning-based joint scheduling and resource management," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 10, pp. 3144–3159, Oct. 2021.
- [92] L. Feng, Y. Zhao, S. Guo, X. Qiu, W. Li, and P. Yu, "BAFL: A blockchain-based asynchronous federated learning framework," *IEEE Trans. Comput.*, vol. 71, no. 5, pp. 1092–1103, May 2022.
- [93] L. Cui et al., "Security and privacy-enhanced federated learning for anomaly detection in IoT infrastructures," *IEEE Trans. Ind. Informat.*, vol. 18, no. 5, pp. 3492–3500, May 2022.
- [94] R. Zeng, C. Zeng, X. Wang, B. Li, and X. Chu, "A comprehensive survey of incentive mechanism for federated learning," Jun. 2021, *arXiv:2106.15406*.
- [95] Y. Liu and J. Wei, "Incentives for federated learning: A hypothesis elicitation approach," Jul. 2020, *arXiv:2007.10596*.
- [96] S. R. Pandey, N. H. Tran, M. Bennis, Y. K. Tun, A. Manzoor, and C. S. Hong, "A crowdsourcing framework for on-device federated learning," *IEEE Trans. Wireless Commun.*, vol. 19, no. 5, pp. 3241–3256, May 2020.
- [97] L. U. Khan et al., "Federated learning for edge networks: Resource optimization and incentive mechanism," *IEEE Commun. Mag.*, vol. 58, no. 10, pp. 88–93, Oct. 2020.
- [98] Y. Jiao, P. Wang, D. Niyato, B. Lin, and D. I. Kim, "Toward an automated auction framework for wireless federated learning services market," *IEEE Trans. Mobile Comput.*, vol. 20, no. 10, pp. 3034–3048, Oct. 2021.
- [99] J. Kang, Z. Xiong, D. Niyato, S. Xie, and J. Zhang, "Incentive mechanism for reliable federated learning: A joint optimization approach to combining reputation and contract theory," *IEEE Internet Things J.*, vol. 6, no. 6, pp. 10700–10714, Dec. 2019.
- [100] W. Y. B. Lim et al., "Towards federated learning in UAV-enabled Internet of Vehicles: A multi-dimensional contract-matching approach," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 8, pp. 5140–5154, Aug. 2021.
- [101] T. Wang, J. Rausch, C. Zhang, R. Jia, and D. Song, "A principled approach to data valuation for federated learning," in *Federated Learning*. Cham, Switzerland: Springer, Sep. 2020, pp. 153–167.
- [102] Y. Zhan, P. Li, Z. Qu, D. Zeng, and S. Guo, "A learning-based incentive mechanism for federated learning," *IEEE Internet Things J.*, vol. 7, no. 7, pp. 6360–6368, Jul. 2020.
- [103] Y. Liu, S. Sun, Z. Ai, S. Zhang, Z. Liu, and H. Yu, "FedCoin: A peer-to-peer payment system for federated learning," in *Federated Learning (Lecture Notes in Computer Science)*. Cham, Switzerland: Springer, Feb. 2020, pp. 125–138.
- [104] T. Yu, E. Bagdasaryan, and V. Shmatikov, "Salvaging federated learning by local adaptation," Feb. 2020, *arXiv:2002.04758*.
- [105] C.-H. Hong and B. Varghese, "Resource management in fog/edge computing: A survey on architectures, infrastructure, and algorithms," *ACM Comput. Surveys*, vol. 52, no. 5, pp. 1–37, 2020.
- [106] D. T. Nguyen, L. B. Le, and V. K. Bhargava, "A market-based framework for multi-resource allocation in fog computing," *IEEE/ACM Trans. Netw.*, vol. 27, no. 3, pp. 1151–1164, Jun. 2019.
- [107] J. Liu, Y. Mao, J. Zhang, and K. B. Letaief, "Delay-optimal computation task scheduling for mobile-edge computing systems," in *Proc. IEEE Int. Symp. Infor. Theory (ISIT)*, Jul. 2016, pp. 1451–1455.
- [108] J. Xu, L. Chen, and S. Ren, "Online learning for offloading and autoscaling in energy harvesting mobile edge computing," *IEEE Trans. Cogn. Commun. Netw.*, vol. 3, no. 3, pp. 361–373, Sep. 2017.
- [109] G. Weiss, *Multiagent Systems: A Modern Approach to Distributed Artificial Intelligence*. Cambridge, MA, USA: MIT Press, 1999.
- [110] L. Busoniu, R. Babuska, and B. De Schutter, "A comprehensive survey of multiagent reinforcement learning," *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 38, no. 2, pp. 156–172, Mar. 2008.
- [111] S. Yu, X. Wang, and R. Langar, "Computation offloading for mobile edge computing: A deep learning approach," in *Proc. IEEE 28th Annu. Int. Symp. Pers., Indoor, Mobile Radio Commun. (PIMRC)*, Oct. 2017, pp. 1–6.
- [112] S. Yu, X. Chen, L. Yang, D. Wu, M. Bennis, and J. Zhang, "Intelligent edge: Leveraging deep imitation learning for mobile edge computation offloading," *IEEE Wireless Commun.*, vol. 27, no. 1, pp. 92–99, Feb. 2020.
- [113] X. Liu, J. Yu, Z. Feng, and Y. Gao, "Multi-agent reinforcement learning for resource allocation in IoT networks with edge computing," *China Commun.*, vol. 17, no. 9, pp. 220–236, Sep. 2020.
- [114] Y. S. Nasir and D. Guo, "Multi-agent deep reinforcement learning for dynamic power allocation in wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 10, pp. 2239–2250, Oct. 2019.
- [115] Z. Ali, L. Jiao, T. Baker, G. Abbas, Z. H. Abbas, and S. Khaf, "A deep learning approach for energy efficient computational offloading in mobile edge computing," *IEEE Access*, vol. 7, pp. 149623–149633, 2019.
- [116] X. Wang, Z. Ning, and S. Guo, "Multi-agent imitation learning for pervasive edge computing: A decentralized computation offloading algorithm," *IEEE Trans. Parallel Distrib. Syst.*, vol. 32, no. 2, pp. 411–425, Feb. 2021.
- [117] X. Chen, C. Wu, Z. Liu, N. Zhang, and Y. Ji, "Computation offloading in beyond 5G networks: A distributed learning framework and applications," *IEEE Wireless Commun.*, vol. 28, no. 2, pp. 56–62, Apr. 2021.
- [118] W. Zhan et al., "Deep-reinforcement-learning-based offloading scheduling for vehicular edge computing," *IEEE Internet Things J.*, vol. 7, no. 6, pp. 5449–5465, Jun. 2020.
- [119] S. Ranadheera, S. Maghsudi, and E. Hossain, "Mobile edge computation offloading using game theory and reinforcement learning," Nov. 2017, *arXiv:1711.09012*.

- [120] Z. Ning, P. Dong, X. Wang, J. J. P. C. Rodrigues, and F. Xia, "Deep reinforcement learning for vehicular edge computing," *ACM Trans. Intell. Syst. Technol.*, vol. 10, no. 6, pp. 1–24, 2019.
- [121] J. Yan, S. Bi, and Y. J. A. Zhang, "Offloading and resource allocation with general task graph in mobile edge computing: A deep reinforcement learning approach," *IEEE Trans. Wireless Commun.*, vol. 19, no. 8, pp. 5404–5419, Aug. 2020.
- [122] L. Huang, S. Bi, and Y.-J. A. Zhang, "Deep reinforcement learning for online computation offloading in wireless powered mobile-edge computing networks," *IEEE Trans. Mobile Comput.*, vol. 19, no. 11, pp. 2581–2593, Nov. 2020.
- [123] J. Chen, S. Chen, Q. Wang, B. Cao, G. Feng, and J. Hu, "iRAF: A deep reinforcement learning approach for collaborative mobile edge computing IoT networks," *IEEE Internet Things J.*, vol. 6, no. 4, pp. 7011–7024, Aug. 2019.
- [124] T. M. Ho and K.-K. Nguyen, "Joint server selection, cooperative offloading and handover in multi-access edge computing wireless network: A deep reinforcement learning approach," *IEEE Trans. Mobile Comput.*, vol. 21, no. 7, pp. 2421–2435, Jul. 2022.
- [125] S. Bi, L. Huang, H. Wang, and Y.-J. A. Zhang, "Lyapunov-guided deep reinforcement learning for stable online computation offloading in mobile-edge computing networks," *IEEE Trans. Wireless Commun.*, vol. 20, no. 11, pp. 7519–7537, Nov. 2021.
- [126] J. Wang, J. Hu, G. Min, A. Y. Zomaya, and N. Georgalas, "Fast adaptive task offloading in edge computing based on meta reinforcement learning," *IEEE Trans. Parallel Distrib. Syst.*, vol. 32, no. 1, pp. 242–253, Jan. 2021.
- [127] X. Qiu, W. Zhang, W. Chen, and Z. Zheng, "Distributed and collective deep reinforcement learning for computation offloading: A practical perspective," *IEEE Trans. Parallel Distrib. Syst.*, vol. 32, no. 5, pp. 1085–1101, May 2021.
- [128] H. Y. Ong, K. Chavez, and A. Hong, "Distributed deep Q-learning," Aug. 2015, *arXiv:1508.04186*.
- [129] M. Tang and V. W. S. Wong, "Deep reinforcement learning for task offloading in mobile edge computing systems," *IEEE Trans. Mobile Comput.*, vol. 21, no. 6, pp. 1985–1997, Jun. 2022.
- [130] Y. Xu, A. Feriani, and E. Hossain, "Decentralized multi-agent reinforcement learning for task offloading under uncertainty," 2021, *arXiv:2107.08114*.
- [131] R. Amiri, H. Mehrpouyan, L. Fridman, R. K. Mallik, A. Nallanathan, and D. Matolak, "A machine learning approach for power allocation in HetNets considering QoS," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2018, pp. 1–7.
- [132] X. Huang, S. Leng, S. Maharjan, and Y. Zhang, "Multi-agent deep reinforcement learning for computation offloading and interference coordination in small cell networks," *IEEE Trans. Veh. Technol.*, vol. 70, no. 9, pp. 9282–9293, Sep. 2021.
- [133] A. Sacco, F. Esposito, G. Marchetto, and P. Montuschi, "Sustainable task offloading in UAV networks via multi-agent reinforcement learning," *IEEE Trans. Veh. Technol.*, vol. 70, no. 5, pp. 5003–5015, May 2021.
- [134] Y. Zhang, B. Di, Z. Zheng, J. Lin, and L. Song, "Distributed multi-cloud multi-access edge computing by multi-agent reinforcement learning," *IEEE Trans. Wireless Commun.*, vol. 20, no. 4, pp. 2565–2578, Apr. 2021.
- [135] H. Gao, X. Wang, X. Ma, W. Wei, and S. Mumtaz, "Com-DDPG: A multiagent reinforcement learning-based offloading strategy for mobile edge computing," Dec. 2020, *arXiv:2012.05105*.
- [136] X. Chen et al., "Age of information aware radio resource management in vehicular networks: A proactive deep reinforcement learning perspective," *IEEE Trans. Wireless Commun.*, vol. 19, no. 4, pp. 2268–2281, Apr. 2020.
- [137] Y. Zhan, S. Guo, P. Li, and J. Zhang, "A deep reinforcement learning based offloading game in edge computing," *IEEE Trans. Comput.*, vol. 69, no. 6, pp. 883–893, Jun. 2020.
- [138] H. H. Zhuo, W. Feng, Y. Lin, Q. Xu, and Q. Yang, "Federated deep reinforcement learning," Jan. 2019, *arXiv:1901.08277*.
- [139] J. Qi, Q. Zhou, L. Lei, and K. Zheng, "Federated reinforcement learning: Techniques, applications, and open challenges," Aug. 2021, *arXiv:2108.11887*.
- [140] X. Wang, Y. Han, C. Wang, Q. Zhao, X. Chen, and M. Chen, "In-edge AI: Intelligentizing mobile edge computing, caching and communication by federated learning," *IEEE Netw.*, vol. 33, no. 5, pp. 156–165, Sep./Oct. 2019.
- [141] S. Shen, Y. Han, X. Wang, and Y. Wang, "Computation offloading with multiple agents in edge-computing-supported IoT," *ACM Trans. Sens. Netw.*, vol. 16, no. 1, pp. 1–27, Feb. 2020.
- [142] W. Hou, H. Wen, H. Song, W. Lei, and W. Zhang, "Multiagent deep reinforcement learning for task offloading and resource allocation in cybertwin-based networks," *IEEE Internet Things J.*, vol. 8, no. 22, pp. 16256–16268, Nov. 2021.
- [143] S. B. Prathiba, G. Raja, S. Anbalagan, K. Dev, S. Gurumoorthy, and A. P. Sankaran, "Federated learning empowered computation offloading and resource management in 6G-V2X," *IEEE Trans. Netw. Sci. Eng.*, vol. 9, no. 5, pp. 3234–3243, Sep./Oct. 2022.
- [144] Z. Wang, T. Lv, and Z. Chang, "Computation offloading and resource allocation based on distributed deep learning and software defined mobile edge computing," *Comput. Netw.*, vol. 205, Mar. 2022, Art. no. 108732.
- [145] S. He, X. Lyu, W. Ni, H. Tian, R. P. Liu, and E. Hossain, "Virtual service placement for edge computing under finite memory and bandwidth," *IEEE Trans. Commun.*, vol. 68, no. 12, pp. 7702–7718, Dec. 2020.
- [146] J. Wang, C. Jiang, H. Zhang, Y. Ren, K.-C. Chen, and L. Hanzo, "Thirty years of machine learning: The road to Pareto-optimal wireless networks," *IEEE Commun. Surveys Tuts.*, vol. 22, no. 3, pp. 1472–1514, 3rd Quart., 2020.
- [147] J. Park, S. Samarakoon, M. Bennis, and M. Debbah, "Wireless network intelligence at the edge," *Proc. IEEE*, vol. 107, no. 11, pp. 2204–2239, Nov. 2019.
- [148] Z. Wang, M. Song, Z. Zhang, Y. Song, Q. Wang, and H. Qi, "Beyond inferring class representatives: User-level privacy leakage from federated learning," in *Proc. IEEE Conf. Comput. Commun. (INFOCOM)*, Apr. 2019, pp. 2512–2520.
- [149] L. Zhu and S. Han, "Deep leakage from gradients," in *Federated Learning*. Cham, Switzerland: Springer, 2020, pp. 17–31.
- [150] W. Xia, W. Wen, K.-K. Wong, T. Q. Quek, J. Zhang, and H. Zhu, "Federated-learning-based client scheduling for low-latency wireless communications," *IEEE Wireless Commun.*, vol. 28, no. 2, pp. 32–38, Apr. 2021.
- [151] M. M. Amiri, D. Gündüz, S. R. Kulkarni, and H. V. Poor, "Convergence of update aware device scheduling for federated learning at the wireless edge," *IEEE Trans. Wireless Commun.*, vol. 20, no. 6, pp. 3643–3658, Jun. 2021.
- [152] J. Ren, Y. He, D. Wen, G. Yu, K. Huang, and D. Guo, "Scheduling for cellular federated edge learning with importance and channel awareness," *IEEE Trans. Wireless Commun.*, vol. 19, no. 11, pp. 7690–7703, Nov. 2020.
- [153] Y. Cui, K. Cao, G. Cao, M. Qiu, and T. Wei, "Client scheduling and resource management for efficient training in heterogeneous IoT-edge federated learning," *IEEE Trans. Comput.-Aided Des. Integr. Circuits Syst.*, vol. 41, no. 8, pp. 2407–2420, Aug. 2022.
- [154] T. T. Vu, D. T. Ngo, H. Q. Ngo, M. N. Dao, N. H. Tran, and R. H. Middleton, "User selection approaches to mitigate the straggler effect for federated learning on cell-free massive MIMO networks," Sep. 2020, *arXiv:2009.02031*.
- [155] H. H. Yang, A. Arafa, T. Q. S. Quek, and H. V. Poor, "Age-based scheduling policy for federated learning in mobile edge networks," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, May 2020, pp. 8743–8747.
- [156] T. Huang, W. Lin, W. Wu, L. He, K. Li, and A. Zomaya, "An efficiency-boosting client selection scheme for federated learning with fairness guarantee," *IEEE Trans. Parallel Distrib. Syst.*, vol. 32, no. 7, pp. 1552–1564, Jul. 2021.
- [157] Y. J. Cho, J. Wang, and G. Joshi, "Client selection in federated learning: Convergence analysis and power-of-choice selection strategies," Oct. 2020, *arXiv:2010.01243*.
- [158] H. H. Yang, Z. Liu, T. Q. S. Quek, and H. V. Poor, "Scheduling policies for federated learning in wireless networks," *IEEE Trans. Commun.*, vol. 68, no. 1, pp. 317–333, Jan. 2020.
- [159] T. Nishio and R. Yonetani, "Client selection for federated learning with heterogeneous resources in mobile edge," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Apr. 2018, pp. 1–7.
- [160] K. Yang, T. Jiang, Y. Shi, and Z. Ding, "Federated learning via over-the-air computation," *IEEE Trans. Wireless Commun.*, vol. 19, no. 3, pp. 2022–2035, Mar. 2020.

- [161] M. M. Amiri and D. Gunduz, "Federated learning over wireless fading channels," *IEEE Trans. Wireless Commun.*, vol. 19, no. 5, pp. 3546–3557, May 2020.
- [162] J. Kang, Z. Xiong, D. Niyato, Y. Zou, Y. Zhang, and M. Guizani, "Reliable federated learning for mobile networks," *IEEE Wireless Commun.*, vol. 27, no. 2, pp. 72–80, Apr. 2020.
- [163] X. Ma, H. Sun, Q. Wang, and R. Q. Hu, "User scheduling for federated learning through over-the-air computation," in *Proc. IEEE 94th Veh. Technol. Conf. (VTC-Fall)*, Sep. 2021, pp. 1–5.
- [164] B. Yin, Z. Chen, and M. Tao, "Joint user scheduling and resource allocation for federated learning over wireless networks," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2020, pp. 1–6.
- [165] M. Chen, Z. Yang, W. Saad, C. Yin, H. V. Poor, and S. Cui, "A joint learning and communications framework for federated learning over wireless networks," *IEEE Trans. Wireless Commun.*, vol. 20, no. 1, pp. 269–283, Jan. 2021.
- [166] T. Zeng, O. Semiari, M. Mozaffari, M. Chen, W. Saad, and M. Bennis, "Federated learning in the sky: Joint power allocation and scheduling with UAV swarms," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2020, pp. 1–8.
- [167] X. Ma, H. Sun, and R. Q. Hu, "Scheduling policy and power allocation for federated learning in NOMA based MEC," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2020, pp. 1–6.
- [168] W. Shi, S. Zhou, Z. Niu, M. Jiang, and L. Geng, "Joint device scheduling and resource allocation for latency constrained wireless federated learning," *IEEE Trans. Wireless Commun.*, vol. 20, no. 1, pp. 453–467, Jan. 2021.
- [169] Q. Zeng, Y. Du, K. Huang, and K. K. Leung, "Energy-efficient radio resource allocation for federated edge learning," in *Proc. IEEE Int. Conf. Commun. Workshops (ICC Workshops)*, Jun. 2020, pp. 1–6.
- [170] N. Yoshida, T. Nishio, M. Morikura, and K. Yamamoto, "MAB-based client selection for federated learning with uncertain resources in mobile networks," in *Proc. IEEE Globecom Workshops (GC Wkshps)*, Sep. 2020, pp. 1–6.
- [171] W. Xia, T. Q. S. Quek, K. Guo, W. Wen, H. H. Yang, and H. Zhu, "Multi-armed bandit based client scheduling for federated learning," *IEEE Trans. Wireless Commun.*, vol. 19, no. 11, pp. 7108–7123, Nov. 2020.
- [172] Y. J. Cho, S. Gupta, G. Joshi, and O. Yağan, "Bandit-based communication-efficient client selection strategies for federated learning," in *Proc. IEEE 54th Asilomar Conf. Signals, Syst., Comput.*, Nov. 2020, pp. 1066–1069.
- [173] B. Xu, W. Xia, J. Zhang, T. Q. S. Quek, and H. Zhu, "Online client scheduling for fast federated learning," *IEEE Wireless Commun. Lett.*, vol. 10, no. 7, pp. 1434–1438, Jul. 2021.
- [174] T. Sery and K. Cohen, "On analog gradient descent learning over multiple access fading channels," *IEEE Trans. Signal Process.*, vol. 68, pp. 2897–2911, Apr. 2020.
- [175] Y. Shao, D. Gunduz, and S. C. Liew, "Federated edge learning with misaligned over-the-air computation," *IEEE Trans. Wireless Commun.*, vol. 21, no. 6, pp. 3951–3964, Jun. 2022.
- [176] M. M. Amiri, T. M. Duman, and D. Gündüz, "Collaborative machine learning at the wireless edge with blind transmitters," in *Proc. IEEE Global Conf. Signal Inf. Process. (GlobalSIP)*, Nov. 2019, pp. 1–5.
- [177] M. M. Amiri, T. M. Duman, D. Gündüz, S. R. Kulkarni, and H. V. Poor, "Blind federated edge learning," *IEEE Trans. Wireless Commun.*, vol. 20, no. 8, pp. 5129–5143, Aug. 2021.
- [178] G. Zhu, Y. Wang, and K. Huang, "Broadband analog aggregation for low-latency federated edge learning," *IEEE Trans. Wireless Commun.*, vol. 19, no. 1, pp. 491–506, Jan. 2020.
- [179] G. Zhu, Y. Du, D. Gunduz, and K. Huang, "One-bit over-the-air aggregation for communication-efficient federated edge learning: Design and convergence analysis," *IEEE Trans. Wireless Commun.*, vol. 20, no. 3, pp. 2120–2135, Mar. 2021.
- [180] T. Sery, N. Shlezinger, K. Cohen, and Y. C. Eldar, "Over-the-air federated learning from heterogeneous data," *IEEE Trans. Signal Process.*, vol. 69, pp. 3796–3811, Jun. 2021.
- [181] Y. Sun, S. Zhou, and D. Gündüz, "Energy-aware analog aggregation for federated learning with redundant data," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jul. 2020, pp. 1–7.
- [182] E. P. Xing et al., "Petuum: A new platform for distributed machine learning on big data," *IEEE Trans. Big Data*, vol. 1, no. 2, pp. 49–67, Jun. 2015.
- [183] M. Li, D. G. Andersen, A. J. Smola, and K. Yu, "Communication efficient distributed machine learning with the parameter server," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 27, 2014, pp. 19–27.
- [184] F. Seide, H. Fu, J. Droppo, G. Li, and D. Yu, "1-bit stochastic gradient descent and its application to data-parallel distributed training of speech DNNs," in *Proc. 15th Annu. Conf. Int. Speech Commun. Assoc.*, 2014, pp. 1058–1062.
- [185] D. Alistarh, J. Li, R. Tomioka, and M. Vojnovic, "QSGD: Randomized quantization for communication-optimal stochastic gradient descent," Oct. 2016, *arXiv:1610.02132*.
- [186] W. Wen et al., "TernGrad: Ternary gradients to reduce communication in distributed deep learning," May 2017, *arXiv:1705.07878*.
- [187] S. Zhou, Y. Wu, Z. Ni, X. Zhou, H. Wen, and Y. Zou, "DoReFNet: Training low bitwidth convolutional neural networks with low bitwidth gradients," Jun. 2016, *arXiv:1606.06160*.
- [188] N. Strom, "Scalable distributed DNN training using commodity GPU cloud computing," in *Proc. 16th Annu. Conf. Int. Speech Commun. Assoc.*, 2015, pp. 1–5.
- [189] A. F. Aji and K. Heafield, "Sparse communication for distributed gradient descent," Apr. 2017, *arXiv:1704.05021*.
- [190] N. Dryden, T. Moon, S. A. Jacobs, and B. Van Essen, "Communication quantization for data-parallel training of deep neural networks," in *Proc. 2nd Workshop Mach. Learn. HPC Environ. (MLHPC)*, Nov. 2016, pp. 1–8.
- [191] C.-Y. Chen, J. Choi, D. Brand, A. Agrawal, W. Zhang, and K. Gopalakrishnan, "AdaComp: Adaptive residual gradient compression for data-parallel distributed training," in *Proc. AAAI Conf. Artif. Intell.*, vol. 32, Apr. 2018, pp. 2827–2835.
- [192] Y. Lin, S. Han, H. Mao, Y. Wang, and W. J. Dally, "Deep gradient compression: Reducing the communication bandwidth for distributed training," Dec. 2017, *arXiv:1712.01887*.
- [193] W. Jiang, B. Han, M. A. Habibi, and H. D. Schotten, "The road towards 6G: A comprehensive survey," *IEEE Open J. Commun. Soc.*, vol. 2, pp. 334–366, 2021.
- [194] T. Bai and R. W. Heath, "Coverage and rate analysis for millimeter-wave cellular networks," *IEEE Trans. Wireless Commun.*, vol. 14, no. 2, pp. 1100–1114, Feb. 2015.
- [195] L. Lu, G. Y. Li, A. L. Swindlehurst, A. Ashikhmin, and R. Zhang, "An overview of massive MIMO: Benefits and challenges," *IEEE J. Sel. Topics Signal Process.*, vol. 8, no. 5, pp. 742–758, Oct. 2014.
- [196] Q. Wu and R. Zhang, "Towards smart and reconfigurable environment: Intelligent reflecting surface aided wireless network," *IEEE Commun. Mag.*, vol. 58, no. 1, pp. 106–112, Jan. 2020.
- [197] L. Dai, R. Jiao, F. Adachi, H. V. Poor, and L. Hanzo, "Deep learning for wireless communications: An emerging interdisciplinary paradigm," *IEEE Wireless Commun.*, vol. 27, no. 4, pp. 133–139, Aug. 2020.
- [198] H. Huang et al., "Deep learning for physical-layer 5G wireless techniques: Opportunities, challenges and solutions," *IEEE Wireless Commun.*, vol. 27, no. 1, pp. 214–222, Feb. 2020.
- [199] H. He, S. Jin, C.-K. Wen, F. Gao, G. Y. Li, and Z. Xu, "Model-driven deep learning for physical layer communications," *IEEE Wireless Commun.*, vol. 26, no. 5, pp. 77–83, Oct. 2019.
- [200] Y.-H. Chen, T. Krishna, J. S. Emer, and V. Sze, "Eyeriss: An energy-efficient reconfigurable accelerator for deep convolutional neural networks," *IEEE J. Solid-State Circuits*, vol. 52, no. 1, pp. 127–138, Jan. 2017.
- [201] T. O'Shea and J. Hoydis, "An introduction to deep learning for the physical layer," *IEEE Trans. Cogn. Commun. Netw.*, vol. 3, no. 4, pp. 563–575, Dec. 2017.
- [202] J. R. Hershey, J. L. Roux, and F. Weninger, "Deep unfolding: Model-based inspiration of novel deep architectures," Sep. 2014, *arXiv:1409.2574*.
- [203] M. Borgerding and P. Schniter, "Onsager-corrected deep learning for sparse linear inverse problems," in *Proc. IEEE Global Conf. Signal Inf. Process. (GlobalSIP)*, Dec. 2016, pp. 227–231.
- [204] C.-K. Wen, W.-T. Shih, and S. Jin, "Deep learning for massive MIMO CSI feedback," *IEEE Wireless Commun. Lett.*, vol. 7, no. 5, pp. 748–751, Oct. 2018.
- [205] A. K. Nandi and E. E. Azzouz, "Algorithms for automatic modulation recognition of communication signals," *IEEE Trans. Commun.*, vol. 46, no. 4, pp. 431–436, Apr. 1998.

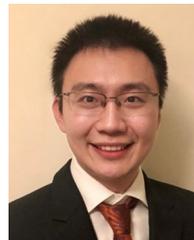
- [206] E. Nachmani, Y. Be'ery, and D. Burshtein, "Learning to decode linear codes using deep learning," in *Proc. IEEE 54th Annu. Allerton Conf. Commun., Control, Comput. (Allerton)*, Sep. 2016, pp. 341–346.
- [207] S. Cammerer, T. Gruber, J. Hoydis, and S. Ten Brink, "Scaling deep learning-based decoding of polar codes via partitioning," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2017, pp. 1–6.
- [208] N. Samuel, T. Diskin, and A. Wiesel, "Deep MIMO detection," in *Proc. IEEE 18th Int. Workshop Signal Process. Adv. Wireless Commun. (SPAWC)*, Jul. 2017, pp. 1–5.
- [209] Z. Qin, H. Ye, G. Y. Li, and B.-H. F. Juang, "Deep learning in physical layer communications," *IEEE Wireless Commun.*, vol. 26, no. 2, pp. 93–99, Apr. 2019.
- [210] T. J. O'Shea, T. Erpek, and T. C. Clancy, "Physical layer deep learning of encodings for the MIMO fading channel," in *Proc. 55th Annu. Allerton Conf. Commun., Control, Comput. (Allerton)*, Oct. 2017, pp. 76–80.
- [211] H. Ye, G. Y. Li, and B.-H. Juang, "Deep learning based end-to-end wireless communication systems without pilots," *IEEE Trans. Cogn. Commun. Netw.*, vol. 7, no. 3, pp. 702–714, Sep. 2021.
- [212] H. Huang, Y. Song, J. Yang, G. Gui, and F. Adachi, "Deep-learning-based millimeter-wave massive MIMO for hybrid precoding," *IEEE Trans. Veh. Technol.*, vol. 68, no. 3, pp. 3027–3032, Mar. 2019.
- [213] C. Qi, Y. Wang, and G. Y. Li, "Deep learning for beam training in millimeter wave massive MIMO systems," *IEEE Trans. Wireless Commun.*, early access, Sep. 22, 2020, doi: 10.1109/TWC.2020.3024279.
- [214] G. Gui, H. Huang, Y. Song, and H. Sari, "Deep learning for an effective nonorthogonal multiple access scheme," *IEEE Trans. Veh. Technol.*, vol. 67, no. 9, pp. 8440–8450, Sep. 2018.
- [215] M. A. Alawad, M. Q. Hamdan, and K. A. Hamdi, "End-to-end deep learning IRS-assisted communications systems," in *Proc. IEEE 94th Veh. Technol. Conf. (VTC-Fall)*, Sep. 2021, pp. 1–6.
- [216] J. Yu, X. Liu, Y. Gao, C. Zhang, and W. Zhang, "Deep learning for channel tracking in IRS-assisted UAV communication systems," *IEEE Trans. Wireless Commun.*, vol. 21, no. 9, pp. 7711–7722, Sep. 2022.
- [217] "Finnish 6G flagship white papers." Jan. 2021. [Online]. Available: <https://www.6gchannel.com/6g-white-papers/>
- [218] T. Paz-Argaman, Y. Atzmon, G. Chechik, and R. Tsarfaty, "ZEST: Zero-shot learning from text descriptions using textual similarity and visual Summarization," Oct. 2020, *arXiv:2010.03276*.
- [219] Y. Zhou, G. Pu, X. Ma, X. Li, and D. Wu, "Distilled one-shot federated learning," Sep. 2020, *arXiv:2009.07999*.
- [220] Z. Chen, S. Maji, and E. Learned-Miller, "Shot in the dark: Few-shot learning with no base-class labels," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, Jun. 2021, pp. 2668–2677.
- [221] M. Huisman, J. N. van Rijn, and A. Plaata, "A survey of deep meta-learning," *Arif. Intell. Rev.*, vol. 54, pp. 4483–4541, Apr. 2021.
- [222] A. Fallah, A. Mokhtari, and A. Ozdaglar, "Personalized federated learning: A meta-learning approach," Feb. 2020, *arXiv:2002.07948*.
- [223] Q. Wu, K. He, and X. Chen, "Personalized federated learning for intelligent IoT applications: A cloud-edge based framework," *IEEE Open J. Comput. Soc.*, vol. 1, pp. 35–44, 2020.
- [224] Y. Zhao, M. Li, L. Lai, N. Suda, D. Civin, and V. Chandra, "Federated learning with non-IID data," Jun. 2018, *arXiv:1806.00582*.
- [225] Y. Koda, J. Park, M. Bennis, K. Yamamoto, T. Nishio, and M. Morikura, "Distributed heteromodal split learning for vision aided mmWave received power prediction," Jul. 2020, *arXiv:2007.08208*.
- [226] K. Yang, Y. Shi, Y. Zhou, Z. Yang, L. Fu, and W. Chen, "Federated machine learning for intelligent IoT via reconfigurable intelligent surface," *IEEE Netw.*, vol. 34, no. 5, pp. 16–22, Sep./Oct. 2020.
- [227] Z. Wang et al., "Federated learning via intelligent reflecting surface," *IEEE Trans. Wireless Commun.*, vol. 21, no. 2, pp. 808–822, Feb. 2022.
- [228] C. Ma et al., "On safeguarding privacy and security in the framework of federated learning," *IEEE Netw.*, vol. 34, no. 4, pp. 242–248, Jul./Aug. 2020.
- [229] R. C. Geyer, T. Klein, and M. Nabi, "Differentially private federated learning: A client level perspective," Dec. 2017, *arXiv:1712.07557*.
- [230] A. Diyanat, A. Khonsari, and S. P. Shariatpanahi, "A dummy-based approach for preserving source rate privacy," *IEEE Trans. Inf. Forensics Security*, vol. 11, pp. 1321–1332, 2016.
- [231] L. T. Phong, Y. Aono, T. Hayashi, L. Wang, and S. Moriai, "Privacy-preserving deep learning via additively homomorphic encryption," *IEEE Trans. Inf. Forensics Security*, vol. 13, pp. 1333–1345, 2017.
- [232] V. Mothukuri, P. Khare, R. M. Parizi, S. Pouriyeh, A. Dehghantanha, and G. Srivastava, "Federated learning-based anomaly detection for IoT security attacks," *IEEE Internet Things J.*, vol. 9, no. 4, pp. 2545–2554, Feb. 2022.



**XIAOLAN LIU** (Member, IEEE) received the Ph.D. degree from the Queen Mary University of London, U.K., in 2021. She was a Research Associate with King's College London from 2020 to 2021. Since October 2021, she has been with the Institute for Digital Technologies, Loughborough University London, U.K., where she is currently a Lecturer. Her current research interests include wireless distributed learning, multiagent reinforcement learning for edge computing, and machine learning for wireless communication optimization.



**JIADONG YU** (Member, IEEE) received the Ph.D. degree from the Queen Mary University of London, U.K., in 2021, where she was a Teaching Fellow in 2021. Since November 2021, she has been with the Internet of Things Thrust, The Hong Kong University of Science and Technology (Guangzhou), where she is currently a Postdoctoral Fellow. Her current research interests include machine learning, deep learning, and federated learning for Internet of Things and wireless communications.



**YUANWEI LIU** (Senior Member, IEEE) received the Ph.D. degree in electrical engineering from the Queen Mary University of London, U.K., in 2016.

He was with the Department of Informatics, King's College London from 2016 to 2017, where he was a Postdoctoral Research Fellow. He has been a Senior Lecturer (Associate Professor) with the School of Electronic Engineering and Computer Science, Queen Mary University of London since August 2021, where he was a Lecturer (Assistant Professor) from 2017 to 2021. His research interests include nonorthogonal multiple access, reconfigurable intelligent surface, integrated sensing and communications, and machine learning. He received the IEEE ComSoc Outstanding Young Researcher Award for EMEA in 2020. He received the 2020 IEEE Signal Processing and Computing for Communications (SPCC) Technical Early Achievement Award and the IEEE Communication Theory Technical Committee 2021 Early Achievement Award. He received IEEE ComSoc Outstanding Nominee for Best Young Professionals Award in 2021. He is the co-recipient of the Best Student Paper Award at IEEE VTC2022-Fall, the Best Paper Award at ISWCS 2022, and the 2022 IEEE SPCC-TC Best Paper Award. He serves as a Senior Editor for IEEE COMMUNICATIONS LETTERS and an Editor for the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS and the IEEE TRANSACTIONS ON COMMUNICATIONS. He serves as the Guest Editor for IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS on Next Generation Multiple Access, IEEE JOURNAL OF SELECTED TOPICS IN SIGNAL PROCESSING on Signal Processing Advances for Non-Orthogonal Multiple Access, and IEEE NETWORK on Next Generation Multiple Access for 6G. He serves as the Publicity Co-Chair for IEEE VTC 2019-Fall and the Symposium Co-Chair for Cognitive Radio and AI-Enabled Networks for IEEE GLOBECOM 2022 and Communication Theory for IEEE GLOBECOM 2023. He serves as the Chair of Special Interest Group (SIG) in SPCC Technical Committee on Signal Processing Techniques for Next Generation Multiple Access and the Vice-Chair of SIG WTC on Reconfigurable Intelligent Surfaces for Smart Radio Environments. He has been a Web of Science Highly Cited Researcher since 2021, an IEEE Communication Society Distinguished Lecturer, an IEEE Vehicular Technology Society Distinguished Lecturer, and the Academic Chair for the Next Generation Multiple Access Emerging Technology Initiative.



**YUE GAO** (Senior Member, IEEE) received the Ph.D. degree from the Queen Mary University of London (QMUL), U.K., in 2007. He is a Chair Professor with the School of Computer Science, Fudan University, China, and a Visiting Professor with the University of Surrey, U.K. He worked as a Lecturer, a Senior Lecturer, a Reader, and the Chair Professor with QMUL and the University of Surrey, respectively. He has published over 200 peer-reviewed journal and conference papers and had over 6600 citations. His research interests

include smart antennas, sparse signal processing, and cognitive networks for mobile and satellite systems. He was a co-recipient of the EU Horizon Prize Award on Collaborative Spectrum Sharing in 2016 and elected as an Engineering and Physical Sciences Research Council Fellow in 2017. He is a member of the Board of Governors and a Distinguished Speaker of the IEEE Vehicular Technology Society (VTS), the Chair of the IEEE ComSoc Wireless Communication Technical Committee, and the Past Chair of the IEEE ComSoc Technical Committee on Cognitive Networks. He has been an editor of several IEEE TRANSACTIONS and journals, and the symposia chair, the track chair, and other roles in the organizing committee of several IEEE ComSoC, VTS, and other conferences.



**SANGARAPILLAI LAMBOTHARAN** (Senior Member, IEEE) received the Ph.D. degree in signal processing from Imperial College London, U.K., in 1997. He was a Visiting Scientist with the Engineering and Theory Centre, Cornell University, USA, in 1996. Until 1999, he was a Postdoctoral Research Associate with Imperial College London. From 1999 to 2002, he was with Motorola Applied Research Group, U.K., where he investigated various projects, including physical link layer modeling and performance characterization of GPRS, EGPRS, and UTRAN. He was with King's College London and Cardiff University as a Lecturer and a Senior Lecturer, respectively, from 2002 to 2007. He is currently a Professor of Signal Processing and Communications and the Director of the Institute for Digital Technologies, Loughborough University London, U.K. His current research interests include 5G networks, MIMO, blockchain, machine learning, and network security. He has authored more than 250 journal articles and conference papers in these areas. He serves as an Associate Editor for the IEEE TRANSACTIONS ON SIGNAL PROCESSING and IEEE TRANSACTIONS ON COMMUNICATIONS. He is a Fellow of IET.



**TOKTAM MAHMOODI** (Senior Member, IEEE) received the B.Sc. degree in electrical engineering from the Sharif University of Technology, Iran, in 2002, and the Ph.D. degree in telecommunications from King's College London, U.K., in 2009. She was a Visiting Research Scientist with F5 Networks, San Jose, CA, USA, in 2013, a Postdoctoral Research Associate with the ISN Research Group, Electrical and Electronic Engineering Department, Imperial College London from 2010 to 2011, and a Mobile VCE Researcher

from 2006 to 2009. She has also worked in the mobile and personal communications industry from 2002 to 2006, and in a research and development team on developing DECT standard for WLL applications. She has contributed to and led a number of FP7, H2020, and EPSRC-funded projects, advancing mobile and wireless communication networks. She is currently the Head of the Centre for Telecommunications Research, Department of Engineering, King's College London, where she is a Professor of Communication Engineering. Her research interests include network intelligence, and mission-critical networking, with impact in healthcare, automotive, smart cities, and emergency services.



**DANNY HIN-KWOK TSANG** (Life Fellow, IEEE) received the Ph.D. degree in electrical engineering from the Moore School of Electrical Engineering, University of Pennsylvania, Philadelphia, PA, USA, in 1989. After graduation, he joined the Department of Computer Science, Dalhousie University, Halifax, NS, Canada. He later joined the Department of Electronic and Computer Engineering, The Hong Kong University of Science and Technology (HKUST), Hong Kong, in 1992, where he is currently a Professor. He has

also been serving as the Thrust Head of the Internet of Things Thrust, HKUST (Guangzhou), Guangzhou, China, since 2020. During his leave from HKUST from 2000 to 2001, he assumed the role of Principal Architect with Sycamore Networks, Chelmsford, MA, USA. His current research interests include cloud computing, edge computing, NOMA networks, and smart grids. He was a Guest Editor of the IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS' special issue on Advances in P2P Streaming Systems, an Associate Editor of *Journal of Optical Networking* published by the Optical Society of America, and a Guest Editor of IEEE SYSTEMS JOURNAL. He currently serves as a member of the Special Editorial Cases Team of *IEEE Communications Magazine*. He was responsible for the network architecture design of Ethernet MAN/WAN over SONET/DWDM networks. He invented the 64B/65B encoding (U.S. Patent No.: U.S. 6952405 B2) and contributed it to the proposal for Transparent GFP in the T1X1.5 standard that was advanced to become the ITU G.GFP standard. The coding scheme has now been adopted by International Telecommunication Union (ITU)'s Generic Framing Procedure Recommendation GFP-T (ITU-T G.7041/Y.1303) and Interfaces of the Optical Transport Network (ITU-T G.709). He was nominated to become an HKIE Fellow in 2013.