Reconfigurable Intelligent Surface Empowered Over-the-Air Federated Edge Learning

Hang Liu, Zehong Lin, Xiaojun Yuan, and Ying-Jun Angela Zhang

Abstract

Federated edge learning (FEEL) has emerged as a revolutionary paradigm for development of AI services at the edge of 6G wireless networks because it supports collaborative model training for a large number of mobile devices. However, model communication over wireless channels, especially in uplink model uploading of FEEL, has been widely recognized as a bottleneck that critically limits the efficiency of FEEL. Although over-the-air computation can alleviate the excessive cost of radio resources in FEEL model uploading, practical implementations of over-the-air FEEL still suffer from several challenges, including strong straggler issues, large communication overheads, and potential privacy leakage. In this article, we study these challenges in over-the-air FEEL and leverage reconfigurable intelligent surface (RIS) — a key enabler of future wireless systems — to address these challenges. We study the state-of-the-art solutions on RIS-empowered FEEL, and explore the promising research opportunities for adopting RIS to enhance FEEL performance.

Introduction

Sixth-generation (6G) wireless communications are envisioned as intelligent information systems that are both driven by and drivers of artificial intelligence (AI). On one hand, AI will make 6G smart, agile, and able to learn and adapt to the changing network dynamics. On the other hand, the unprecedented capacity and flexibility of 6G will facilitate the deployment of mobile AI services to support diversified computation-intensive mobile applications, such as autonomous driving, auto-robots, and augmented reality. These applications stimulate the development of large-scale machine learning (ML) technologies that can make use of gargantuan amounts of mobile data generated by ever-increasing edge devices.

Moreover, new smart devices exhibit a compelling increase in computation capability, making on-device local training possible for sophisticated AI models. With all that being said, the future wireless networks will be designed to support distributed ML that leverages local resources, including local computation units and data, at the edge level. This calls for revolutionary communication and computation techniques to meet stringent latency and accuracy requirements with limited radio resources such as bandwidth and power.

Edge ML has generated considerable recent research interest; one of the most important approaches is federated learning (FL) [1], which collaboratively trains a unified AI model for different parties without direct data exchange. When FL is deployed at the edge level, known as federated edge learning (FEEL) [2], edge devices perform local training using local data and periodically exchange model information instead of raw data with a parameter server (PS, usually a base station in a wireless network) to update the global model. While FEEL improves the computation efficiency by exploiting the computation capabilities of local devices, frequent model communications between the edge devices and the PS critically limit the performance of FEEL. To see this, note that a FEEL network generally comprises thousands or even millions of edge devices (e.g., smartphones and Internet-of-things (IoT) devices). It is shown that model communication, especially in uplink model uploading, can be slower than local computation by many orders of magnitude due to limited radio resources. Over-the-air computation has been introduced into FEEL to relieve the communication burden of uplink model uploading [2]. Specifically, over-the-air computation allows massive devices to simultaneously upload local models over the same time-frequency resources by exploiting the signal superposition property of multiple-access channels. With over-the-air computation, the latency or the required bandwidth in FEEL model uploading is independent of the number of devices and thus can be vastly reduced.

Although over-the-air FEEL is envisioned to be a scalable solution, there still remain three unresolved challenges that limit its communication performance: First, over-the-air FEEL suffers from an inherent communication-learning trade-off induced by device selection. While selecting a subset of edge devices to participate can improve the communication quality, device selection decreases the number of equipped training data and hence may degrade the learning convergence [2]. Such a conflict puts practical device selection in a dilemma and complicates the design on both communication and learning aspects. Second, the design of over-the-air FEEL critically relies on transmitter-side signal scaling to align the local models coherently at the receiver. This is usually achieved by using channel state information at the transmitter side (CSIT). However, CSIT acquisition requires fre-

1 This article is focused on the uplink model uploading and aggregation of over-the-air FEEL as these two steps are regarded as the main bottlenecks of FEEL. Downlink model broadcasting, however, is another interesting topic that deserves dedicated research efforts.

2 Low-quality data caused by contamination or poisoning attacks jeopardizes the learning convergence and should be discarded, for example, by anomaly detection. However, quality-aware data sampling is beyond the scope of this article.
FIGURE 1. The FEEL workflow.

From the above discussions, we see that all the three remaining challenges in canonical over-the-air FEEL come down to the limitation of the volatile wireless propagation environment. This limitation can be potentially eliminated by the forward-looking vision of “smart radio environment” in future wireless systems. As a key enabler of the smart radio environment, reconfigurable intelligent surface (RIS) perceives wireless propagation channels as programmable entities that can be dynamically configured [3]. Specifically, a RIS is a two-dimensional metasurface consisting of a large number of tiny, low-cost, and passive reflecting elements that can induce adjustable phase shifts to the incident signals [4]. The RIS-enabled wireless networks are thus able to enhance the channel conditions of devices by tuning the RIS phase shifts.

RIS-enhanced communications have already attracted widespread interest in the community. The challenges and developments for RIS-assisted wireless communications can be found in, for example, [3, 4]. While much research has investigated RIS and over-the-air FEEL separately in recent years, limited work has been done toward an integrated design on RIS-assisted over-the-air FEEL. In particular, Ref. [5] made a preliminary investigation on the use of RIS to mitigate the over-the-air model aggregation error. Ref. [6] reported that RIS can efficiently enhance the model aggregation accuracy and balance the communication-learning trade-off in over-the-air FEEL. Ref. [7] utilized RIS to reduce the downlink feedback overhead for over-the-air FEEL. These works have demonstrated the importance of RIS in addressing the first two challenges of over-the-air FEEL, namely the communication-learning trade-off and large communication overheads. Moreover, Ref. [8] has shown that the privacy of FEEL model aggregation is determined by the channel conditions of edge devices. RIS is envisioned to address the privacy leakage issue of over-the-air FEEL thanks to its capability of configuring the wireless channels. However, the above literature considers different setups and focuses on resolving only one specific challenge of over-the-air FEEL. To better investigate the effect of RIS on over-the-air FEEL, we need a unified RIS-assisted model communication framework. Motivated by this, we aim to spur research attention toward the use of RIS in resolving communication bottlenecks of over-the-air FEEL in this article. Different from the existing magazine article [5] that mainly aims to introduce RIS into FEEL systems, we focus on adopting RIS for addressing the three major communication challenges in over-the-air FEEL, namely the communication-learning trade-off, the large overhead in CSIT feedback, and the privacy leakage issue. Specifically, we investigate a unified RIS-empowered FEEL framework, review state-of-the-art efforts in addressing these challenges under this framework, and discuss implementation issues of the current design as well as promising research opportunities.

The remainder of this article is organized as follows. In the next section, we review over-the-air FEEL and point out the three major challenges therein. Following that, we introduce the RIS technique and propose a unified RIS-empowered FEEL framework to address these challenges. Then we discuss the state-of-the-art solutions to each research challenge under the proposed framework. Following that we discuss other research opportunities. Finally, we conclude this article in the final section.

**Over-the-Air FEEL**

A general FEEL system comprises a PS and a number of edge devices in a wireless network, with each device possessing a local training dataset and establishing a channel link with the PS. The edge devices aim to learn a uniform AI model from the local data. That is, the goal is to find an optimal parameter set of a given AI model by minimizing an additive empirical loss function with respect to all local training samples [1].

In FEEL, each device trains a local model that minimizes the local loss function using its on-device data samples. Furthermore, the PS iteratively exchanges model information with the devices until convergence.

Moreover, the acquisition of the latest channel state information (CSI) is critical in FEEL system design. In this regard, in each coherence block we dedicate a number of symbols, a.k.a. communication overhead, for channel estimation before model transmission. As shown in Fig. 1, FEEL in a coherence block involves the following steps:

1. Edge devices send training pilots to the PS to estimate CSI.
2. The PS selects a subset of devices to participate into the learning process.
3. The PS feedbacks the CSI to the devices through downlink control channels.
4. The PS broadcasts the global model to the selected devices.
5. Each selected device updates the local model by using, for example, stochastic gradient descent.
6. The selected devices upload the local gradients or model changes defined as the element-wise difference between the initial model and the trained local model to the PS. The PS aggregates a weighted sum of the local model changes and updates the global model.

Steps 4–6 are repeatedly executed until the end of the coherence block, and the next block begins with Step 1.

112

IEEE Wireless Communications • December 2023
**Over-the-Air Model Aggregation**

A federated learning network generally comprises numerous edge devices. Consequently, concurrently uploading such a massive number of local models through multiple-access wireless channels costs a large amount of radio resources and incurs an excessively long delay. As a result, model uploading and aggregation in Step 6 have been widely recognized as the main bottleneck of FEEL [1]. To tackle the challenge in Step 6, over-the-air computation has been introduced to support a large number of simultaneous model uploading [2]. The over-the-air computation process is illustrated in Fig. 2. In each learning iteration, edge devices transmit local model changes over the same physical channel by following the channel inversion principle. Specifically, each device sets the transmit scaling coefficient as the ratio of the desired model aggregation weight over its instantaneous channel coefficient. By doing this, the channel fading coefficients are canceled at the PS, and the received signal at the PS is a noisy version of the desired linear combination of local models due to the superposition property of the wireless channel. Then, the PS estimates the weighted summation of the local models by receive combining as the updated global model for the next training iteration. As the required bandwidth or latency does not scale with the number of edge devices, the over-the-air computation is deemed to be a scalable solution to model aggregation.

**Major Challenges In Over-the-Air FEEL**

Although over-the-air FEEL alleviates high bandwidth burden in model aggregation, there are still three key challenges yet to be adequately addressed. We elaborate on these challenges here, and motivate our design on RIS-empowered FEEL in the next subsection.

First, the performance of over-the-air model aggregation is limited by the communication-learning trade-off. Specifically, wireless channel conditions vary significantly across mobile devices. Consequently, a straggler issue exists in the sense that the model aggregation performance is dominated by the devices with weak channel qualities, a.k.a. the communication stragglers. This is because the devices with better channel qualities have to lower their transmit power so that signals from all devices are coherently aligned at the PS. In order to limit the model aggregation error, the aforementioned stragglers have to be excluded from model training through device selection in Step 2 of Fig. 1. However, selecting a subset of devices to participate may slow down the learning convergence [2]. Furthermore, in light of heterogeneous data distributions among edge devices, excluding the stragglers exacerbates the convergence rate loss as it causes a bias to the global model aggregation.

The existence of the stragglers leads to a fundamental trade-off between minimizing the communication error and maximizing the number of participants in device selection. This is referred to as the communication-learning trade-off in over-the-air FEEL [3] and is illustrated in Fig. 3. On one hand, Fig. 3a shows that the model aggregation mean-square-error (MSE) significantly increases when more devices participate in training. On the other hand, if the communication error is intention-

![FIGURE 2 The over-the-air model aggregation framework.](image-url)

---

1 The communication-learning trade-off in traditional FEEL usually refers to the trade-off between communication delay and learning performance [1]. In contrast, the communication-learning trade-off in over-the-air FEEL refers to the trade-off between model communication error and the convergence rate, where the two aspects have a coupled impact on the learning performance.

2 Alternatively, the PS can compute and transmit the scaling factors to the devices. This incurs the same signaling overhead as sending CSI to the devices.

---
leads to imperfect signal alignment in over-the-air model aggregation. This challenge is summarized as follows.

C2: To facilitate coherent model aggregation, the PS needs to frequently feedback CSI to the devices. This incurs high downlink signaling overhead and extra signal alignment error.

The last challenge lies in the potential privacy leakage in FEEL. Since over-the-air FEEL needs to share local model information with the PS in the model aggregation process, communicating local models reveals sensitive information and is prone to privacy attacks from an untrusted server. For example, batch-averaged gradients transmitted in learning iterations can be reverse engineered to recover the corresponding training images. Consequently, the private information about local data can be leaked in model aggregation. Therefore, privacy-preserving mechanisms, such as differential privacy (DP), secure multiparty computation, and encryption, are needed to protect the privacy for FEEL. However, these mechanisms often achieve data privacy at the cost of reduced learning performance or additional communication resources. For example, a widely adopted approach in DP is to add independent artificial noises to the local model updates before transmission. This inevitably brings errors to model aggregation and degrades the learning performance. The DP level in over-the-air FEEL is determined by the minimum channel gain, making the system design challenging.

**Overview on RIS-Empowered Over-the-Air FEEL**

To tackle Challenges C1–C3, communication mechanisms in conventional communication systems should be revisited and radio resources should be specifically optimized with respect to FEEL objectives, such as training loss or training time, other than conventional communication metrics. This not only complicates the transceiver design but also increases the radio resource requirements. For example, to address the communication-learning trade-off, an additional device selection procedure, that is, Step 2 of Fig. 1 is required before model transmissions, which increases the computational complexity of system optimization. Besides, in order to enhance the privacy preservation in FEEL by DP, more transmit power is required to introduce artificial noise.

We envision that the above detriments brought in addressing Challenges C1–C3 can be effectively alleviated by an emerging wireless communication technique called RIS. Specifically, a RIS can shape the wireless channel, increasing the system design challenges.

![Diagram](image_url)
without incurring high signal processing complexity nor high power/energy consumption, as detailed in the remaining of this article. We here propose a RIS-empowered FEEL framework illustrated in Fig. 4. The RIS is adopted in assisting the model uploading from the edge devices to the PS. Specifically, by introducing the RIS to FEEL, new device-RIS-PS channel links are created to enhance the existing direct device-PS channel links to improve the channel quality. Furthermore, the newly added device-RIS-PS channel coefficients can be tuned by adjusting the phase shifts induced by the RIS elements. Consequently, the overall channel of each device can be regarded as a function of the RIS phase shift vector and be configured by optimizing it.

The proposed RIS-empowered over-the-air FEEL has the following steps. First, the PS selects active devices in each training round and broadcasts the current model to them. The RIS configurations are optimized at the PS and sent to the RIS controller via separate backhaul links to implement RIS phase shifts [4]. Meanwhile, the transmit scaling factors at the devices are computed by using the effective channel coefficients. Then, the devices transmit their model changes to the PS via over-the-air computation so that they are appropriately added at the PS. Due to the communication-learning trade-off, the transceiver design, the RIS phase shifts, and the device selection should be jointly designed under a unified metric that characterizes both the communication and learning impacts on FEEL. Figure 4 illustrates a typical scenario of RIS-empowered over-the-air FEEL. The PS intends to exploit the model information at several edge devices to maximize the learning convergence rate. However, such devices suffer from large model aggregation errors due to the bad channel conditions of the direct channel links. With the help of the RIS, we can create extra reflection links to enhance the channel conditions of those communication stragglers, and hence the dilemma in the communication-learning trade-off can be broken. We note that the proposed RIS-empowered FEEL framework unifies the existing designs on RIS-enabled FEEL [6, 7, 9, 10]. We shall review the state-of-the-art solutions on RIS-empowered FEEL in addressing Challenges C1–C3 in the subsequent sections.
that RIS-assisted communication-learning co-design leads to noticeable convergence improvement compared with the one without RIS. Moreover, Ref. [6] designed RIS-empowered FEEL by directly analyzing the coupled impact of both aggregation error and device selection loss. It shows that the training loss is upper bounded by a sum of a device selection loss and a communication loss: While the device selection loss decreases when more devices are selected, the communication loss increases when the selected channels are weaker. Furthermore, Ref. [6] jointly optimizes the RIS phase shifts, the receiver beamforming, and the device selection by directly minimizing the overall learning performance loss. Figure 5 plots the learning accuracy of the communication-learning co-design approach in [6] with or without RIS. The RIS phase shifts efficiently enhance the channel conditions and well balance the communication-learning trade-off. As a result, the model aggregation error of the RIS-assisted design is sufficiently small, which does not affect the gradient descent directions in the training process. This result demonstrates the importance of RIS in enhancing the communication-learning co-design in FEEL.

The above approaches suffer from high computational complexity in the high-dimensional optimization of the large RIS phase-shift vector. Possible low-complexity substitution of high-dimensional optimization is a codebook-based RIS design. For example, we can design a RIS phase shift codebook with each codeword beamforms the incident signals to different directions and search for the best RIS configuration codeword. Moreover, recent studies have shown that the RIS design complexity can be significantly reduced by exploiting the channel statistic information for conventional wireless networks [11]. We envision that the channel statistics can also be applied to facilitate the low-complexity communication-learning co-design in over-the-air FEEL. Moreover, we highlight other two possible extensions of the existing RIS-empowered communication-learning co-design. First, the current work in [6, 9, 10] assumes fixed device selection in each coherence block. Note that time-varying device scheduling (i.e., selecting different devices in different iterations) is generally more favorable than the fixed one as the former can exploit diversified training data on different devices. However, time-varying device scheduling significantly complicates the design of RIS-empowered FEEL. Second, as shown in Fig. 3b, the device selection loss is more severe when data are non-identically distributed across devices. In this case, the RIS plays a more profound role in improving the channel qualities of devices with important data so that they do not need to be discarded in device selection. To achieve this goal, system optimization should also consider the impact of the data heterogeneity.

**RIS for Low-overhead Over-the-Air FEEL**

The approaches above all assume perfect CSIT for transmit scaling. However, acquiring CSIT incurs high communication overhead in Step 3 of Fig. 1. Furthermore, the inevitable error in CSI quantization/communication degrades the signal alignment accuracy in model aggregation. Massive multiple-input multiple-output (MIMO) has been utilized to avoid the CSI feedback by achieving CSIT-free transmit scaling [12], but it increases power consumption and deployment costs. As RIS can significantly improve the energy efficiency of wireless communications [31], it is necessary to leverage RIS for achieving CSIT-free FEEL. A recent study in [7] utilized RIS to design CSIT-free FEEL systems. Specifically, it is assumed that no CSIT is available at the devices, and the PS is only equipped with one receive antenna. Consequently, the authors in [7] configured the RIS phase shifts so that the resultant channel coefficient of each device is approximately proportional to the corresponding aggregation weight. In this way, the local model updates are coherently aligned through adjusting channel coefficients via the RIS. Figure 6 plots the performance of the CSIT-free FEEL framework in [7] with various numbers of RIS elements. With a sufficiently large RIS, the RIS-assisted design achieves a sufficiently small model aggregation error, whose effect on the gradient descent direction is negligible. Therefore, it achieves a similar accuracy to the error-free benchmark, demonstrating the power of a passive RIS in attaining low-overhead FEEL.

We note that the CSIT-free FEEL design mentioned above focuses on the communication aspect only without considering device selection. As discussed earlier, communication-learning co-design can further unleash the potential of RIS in empowering FEEL, which remains an open problem in the field of CSIT-free FEEL. We envision low-overhead FEEL with joint device selection and communication design as a promising future research direction. However, the communication-learning co-design for CSIT-free FEEL becomes more challenging than the CSIT-based one since device selection critically affects the capability of signal alignment by the RIS phase shifts. Specifically, aligning dissimilar channel coefficients to the predetermined weight is more difficult and thus usually leads to a large aggregation error. Therefore, device selection should not only balance the communication-learning trade-off but also activate devices with channel coefficients as similar as possible by, for example, channel-aware user grouping. Furthermore, the current RIS-empowered design in [7] relies only on the RIS for signal alignment.
RIS for Private Over-the-Air FEEL

In this section, we study Challenge C3, namely privacy leakage in FEEL. A widely adopted privacy preserving approach, known as DP, is for each device to hide its information, for example, by adding artificial noise. The analyses in [8, 13] reveal the fundamental trade-off between learning performance and privacy level: More artificial noise leads to a higher privacy level but compromises the learning performance of FEEL. As discussed earlier, DP in over-the-air FEEL has a more complicated expression compared with traditional FL, which makes the privacy enhancement of over-the-air FEEL more challenging. Considering that the PS is equipped with multiple antennas, the achievable DP at the PS corresponds to the minimum DP level at the receive antennas, which is determined by the minimum channel gain among all the transmit-receive antenna pairs. Since RIS can efficiently manipulate wireless channels, it is necessary to explore RIS to enhance the DP in model aggregation. Specifically, the role of RIS in DP-aware over-the-air FEEL is to manipulate the wireless channel conditions so that the achievable DP is sufficiently high and, at the same time, the accurate model aggregation is achieved. Analogously to the communication-learning co-design previously discussed, the communication (i.e., transceivers and RIS phase shifts), learning (i.e., device selection), and privacy (i.e., the power of artificial noise and the information retrieval mechanism) aspects shall be jointly optimized in a unified optimization framework. A possible formulation is to minimize the expected training loss subject to $\varepsilon$-DP privacy preservation, that is, the privacy leakage levels at all the receive antennas are below some given threshold $\varepsilon$. To this end, the impacts of the communication-learning-privacy factors on both the training loss and the privacy leakage shall be investigated, and the learning behavior and the DP level shall be modeled with respect to all the considered variables.

Other Opportunities in RIS-Empowered Over-the-Air FEEL

Except for Challenges C1–C3, RIS can also be employed to enhance over-the-air FEEL in the following aspects.

AI-Based Low-Complexity RIS Configuration: Optimizing the RIS phase shifts is extremely challenging when the number of RIS elements becomes large. AI technology is efficient in solving such a large-scale optimization problem. Particularly, the deep reinforcement learning (DRL) technique has been adopted for sum-rate maximization in conventional RIS-assisted wireless networks [14]. Since the relationship between the RIS design and the learning convergence is difficult to model for general non-convex learning tasks, we envision that data-driven AI techniques such as DRL are promising for low-complexity system optimization in RIS-assisted over-the-air FEEL.

RIS Deployment Optimization: The performance of RIS-assisted FEEL systems critically depends on the deployment strategy of the RIS, which is overlooked in the related literature. To combat the large path loss of the cascaded RIS reflecting channels, we need to place the RIS in the region where the LoS links are available for both the device-RIS and the RIS-PS channels. Moreover, since the over-the-air model aggregation is dominated by the communication straggler with the worst channel condition, the RIS should be placed near such a straggler. In summary, the RIS deployment should simultaneously consider the above factors and be jointly optimized with other variables such as device selection in the system design.

RIS for Passive Beamforming and Data Transfer: Recent studies show that RIS can be integrated with sensors to actively sense the data from the environment. Accordingly, we can use RIS to assist over-the-air FEEL and simultaneously gather training data from the environment. It has been verified that sharing a small amount of additional training data among the edge devices can largely enhance the convergence rate of FL. The passive beamforming and information transfer (PBIT) technique [15] can be extended to over-the-air FEEL systems to achieve RIS-assisted model aggregation and data sharing from the RIS to the edge devices.

Conclusions

This article discussed the fundamental communication challenges in over-the-air FEEL systems: the communication-learning trade-off, the large communication overhead, and the privacy leakage issue. We introduced a RIS-empowered FEEL framework to address these challenges and discussed the promising future directions under this framework. We hope this article will spur widespread interest in the integration of FEEL and RIS.

Acknowledgment

This work was supported in part by the National Natural Science Foundation of China (Grant No. 62071090), in part by the Sichuan Science and Technology Program (Grant No. 2022YJ0D0120), the Natural Science Foundation of China (Grant No. 62071090), in part by the Sichuan Science and Technology Program (Grant No. 2022YJ0D0120), and the Sichuan Science and Technology Program (Grant No. 2022YJ0D0120).
and in part by the General Research Fund (project number 14201920, 14202421, 14214122, 14202723), Area of Excellence Scheme grant (project number AoE/E-601/22-R), and NSFC/RGC Collaborative Research Scheme (project number CRS_HKUST603/22), all from the Research Grants Council of Hong Kong.

**References**

[1] B. McMahan et al., “Communication-Efficient Learning of Deep Networks From Decentralized Data,” Proc. 20th Int'l. Conf. Artif. Intell. Stat., vol. 54, Apr. 2017, pp. 1271–82.

[2] G. Zhu, Y. Wang, and K. Huang, “Broadband Analog Aggregation for Low Latency Federated Edge Learning,” IEEE Trans. Wireless Commun., vol. 19, no. 1, Jan. 2020, pp. 491–506.

[3] X. Yuan et al., “Reconfigurable-Intelligent-Surface Empowered Wireless Communications: Challenges and Opportunities,” IEEE Wireless Commun., vol. 28, no. 2, Apr. 2021, pp. 136–43.

[4] Q. Wu et al., “Intelligent Reflecting Surface Aided Wireless Communications: A Tutorial,” IEEE Trans. Commun., vol. 69, no. 5, May 2021, pp. 3313–51.

[5] K. Yang et al., “Federated Machine Learning for Intelligent IoT via Reconfigurable Intelligent Surface,” IEEE Netw., vol. 34, no. 5, Oct. 2020, pp. 16–22.

[6] H. Liu, X. Yuan, and Y.-J. A. Zhang, “Reconfigurable Intelligent Surface Enabled Federated Learning: A Unified Communication-Learning Design Approach,” IEEE Trans. Wireless Commun., vol. 20, no. 11, Nov. 2021, pp. 7595–7609.

[7] H. Liu, X. Yuan, and Y.-J. A. Zhang, “CST-Free Federated Edge Learning via Reconfigurable Intelligent Surface,” IEEE Wireless Commun. Lett., vol. 10, no. 11, Nov. 2021, pp. 2440–44.

[8] K. Wei et al., “Federated Learning With Differential Privacy: Algorithms and Performance Analysis,” IEEE Trans. Inf. Forensics Secur., vol. 15, 2020, pp. 3454–69.

[9] Z. Wang et al., “Federated Learning via Intelligent Reflecting Surface,” IEEE Trans. Wireless Commun., vol. 21, no. 2, Feb. 2022, pp. 808–22.

[10] W. Ni et al., “Federated Learning in Multi-RIS Aided Systems,” IEEE Internet Things J., vol. 9, no. 12, June, 2022, pp. 9608–24.

[11] M.-M. Zhao et al., “Intelligent Reflecting Surface Enhanced Wireless Networks: Two-Timescale Beamforming Optimization,” IEEE Trans. Wireless Commun., vol. 20, no. 1, Jan. 2021, pp. 2–17.

[12] M. M. Amiri et al., “Blind Federated Edge Learning,” IEEE Trans. Wireless Commun., vol. 20, no. 8, Aug. 2021, pp. 5129–43.

[13] D. Liu and O. Simeone, “Privacy for Free: Wireless Federated Learning via Uncoded Transmission With Adaptive Power Control,” IEEE JSAC, vol. 39, no. 1, Jan. 2021, pp. 170–85.

[14] C. Huang, R. Mo, and C. Yuen, “Reconfigurable Intelligent Surface Assisted Multiuser MISO Systems Exploiting Deep Reinforcement Learning,” IEEE JSAC, vol. 38, no. 8, Aug. 2020, pp. 1839–50.

[15] W. Yan et al., “Passive Beamforming and Information Transfer Design for Reconfigurable Intelligent Surfaces Aided Multiuser MIMO Systems,” IEEE JSAC, vol. 38, no. 8, Aug. 2020, pp. 1793–1808.

**Biographies**

**Hang Liu** [S’19, M’21] (bhuhangle@gmail.com) received his B.Sc. and Ph.D. degrees from The Chinese University of Hong Kong.

**Zehong Lin** [S’17] (lz018@ie.cuhk.edu.hk) received his Ph.D. degree in information engineering from The Chinese University of Hong Kong.

**Xiaojun Yuan** [S’04, M’09, SM’15] (xjyuan@uestc.edu.cn) received the Ph.D. degree in Electrical Engineering from the City University of Hong Kong in 2005. From 2009 to 2011, he was a research fellow at the Department of Electronic Engineering, the City University of Hong Kong. He was also a visiting scholar at the Department of Electrical Engineering, the University of Hawaii at Manoa in spring and summer 2009, as well as in the same period of 2010. From 2011 to 2014, he was a research assistant professor with the Institute of Network Coding, The Chinese University of Hong Kong. From 2014 to 2017, he was an assistant professor with the School of Information Science and Technology, ShanghaiTech University. He is now a state-specially-recruited professor with the University of Electronic Science and Technology of China.

**Ying-Jun Angela Zhang** [S’00, M’05, SM’10, F’20] (ypjhang@ie.cuhk.edu.hk) received her Ph.D. degree from the Department of Electrical and Electronic Engineering, The Hong Kong University of Science and Technology. She joined the Department of Information Engineering, The Chinese University of Hong Kong in 2005, where she is now a professor. She is now a Member-at-Large of IEEE ComSoc Board of Governors. She served as the Editor-in-Chief of IEEE Open Journal of the Communications Society, a member of the Steering Committees of IEEE Trans. Mobile Computing, IEEE Wireless Communication Letters, and IEEE NetworkComm Conference.