SWIPT-Empowered Sustainable Wireless Federated Learning: Paradigms, Challenges, and Solutions

Yuan Wu, Minghui Dai, Liping Qian, Zhou Su, Tony Q. S. Quek, and Derrick Wing Kwan Ng

Abstract

Wireless federated learning (FL), which allows edge devices to perform local deep/machine learning (DL/ML) training and further aggregates the locally trained models from them via radio channels, establishes a promising framework for enabling various DL/ML-based services in future B5G/6G networks. Despite respecting the data privacy, periodically performing the local model training is not friendly to energy-constrained edge devices and degrades the sustainability and performance of FL services. In this article, motivated by the advanced simultaneous wireless information and power transfer (SWIPT), we propose a framework of SWIPT-empowered wireless FL that can provide over-the-air wireless power transfer in parallel with the transmission of global/local models. We present the key approaches of leveraging SWIPT for FL with their advantages illustrated. The practical challenging issues in reaping the benefits of integrating SWIPT are then discussed and we also provide the potential solutions to address these issues. A representative case study of FL via SWIPT is presented to validate the advantages of exploiting SWIPT. To this end, we present a joint design of SWIPT policy and the client-scheduling for FL, which is firstly formulated as a finite horizon dynamic optimization problem and then is solved by an actor-critic-based deep reinforcement learning algorithm. We finally articulate some potential open future directions regarding the SWIPT-empowered wireless FL.

Introduction

With the deep penetration of advanced B5G/6G cellular systems into all sectors of human society, the past decades have witnessed an explosive growth of machine learning (ML) and deep learning (DL)-based services and applications, e.g., autonomous driving, edge computing, virtual/augmented reality, etc. [1]. Thanks to the rapidly growing capacity of wireless devices with increasing computational and storage resources, the framework of distributed learning has become a promising solution to enable emerging ML/DL-assisted services in wireless edge networks. In particular, federated learning (FL), as a key paradigm for enabling the distributed ML/DL while respecting the privacy of users' local data, has attracted lots of interests from both academia and industries. Different from the conventional centralized training schemes requiring the collection of users' local data, FL allows a group of wireless devices to train their respective local models and further collects those locally trained models for aggregation, which thus improves the privacy of users' local data. As such, there has been a growing interest in the study of various wireless FL paradigms and the corresponding applications [2], [3], [4], [5].

Despite its potential benefits, FL requires its client devices (e.g., wireless edge devices) to periodically perform local training and further upload the computed local models to the FL server via radio transmission. These periodic operations are generally energy-consuming and shorten the lifetimes of the client devices which are usually energy-limited. For instance, under wild environments without a reliable energy supply, the batteries of smart Internet-of-Things (IoT) terminals would be quickly exhausted when participating in FL, which not only impairs the sustainability of FL services, but also degrades the accuracy of the collective training. Thus, how to balance between the energy consumption of wireless FL and its performance (e.g., convergence accuracy) is with the utmost importance. As a remedy, much effort has been devoted to optimizing the energy efficiency of wireless FL from different perspectives, including resource allocation, FL parameter-configuration, and client-scheduling policy, e.g., [6], [7], [8], [9]. Viewing the growing maturity of the technology of wireless power transfer, several recent studies have focused on improving the energy availability for FL clients by utilizing the technique of wireless power transfer [10], [11], [12].

Motivated by the recent advances in transferring power in parallel with wireless data transmission, in this article, we advocate the application of simultaneous wireless information and power transfer (SWIPT) to facilitate FL [13], in which the radio transmission between the FL server and clients is utilized for the dual use of

Digital Object Identifier: 10.1109/MNET.128.2200344
Date of Current Version: 29 March 2024
Date of Publication: 31 October 2022

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delivering the global/local ML model and transferring power simultaneously. For instance, the FL server can send the global model to the client devices and meanwhile transfer wireless power to them via SWIPT. As such, the client devices can exploit the harvested energy to perform their following local model training and uploading. This approach not only improves the efficiency in utilizing the radio channels, but also effectively increases the client devices' available energy and enhances their capabilities of local training and uploading the trained models to the FL server. Moreover, the recent advances in leveraging ultrahigh spectrums, e.g., the visible light and laser, for wireless data transmission can also be exploited to enable SWIPT for FL, especially in the indoor environment [14].

Leveraging SWIPT for FL, however, necessitates a careful design of wireless charging management and the corresponding allocation of computation/communication resources. For instance, the client device's central processing unit (CPU) frequency for local model training would influence its energy consumption that plays a key role in determining the optimal wireless charging policy in SWIPT networks. Although adopting a longer wireless charging duration enables the devices to harvest more energy to facilitate their operations, it would incur a longer time-overhead for performing SWIPT and thus might adversely influence the FL convergence latency. Therefore, it is an open research direction on how to reap the benefit of SWIPT for FL while accounting for its consequent influence. Our detailed contributions in this article can be summarized as follows.

- We illustrate several key paradigms of leveraging SWIPT that provide over-the-air wireless power transfer concurrently with the transmission of global/local models in FL, depending on the receivers/sources of the transferred energy. The potential advantages of utilizing SWIPT are summarized with various promising application scenarios presented.
- We discuss several challenging issues in achieving the benefits of SWIPT, including the time-overhead, the efficiency of wireless power transfer, the reliability of the harvested energy, and the incentive for providing SWIPT. We also provide the corresponding potential solutions. Open research directions in exploiting SWIPT for wireless FL are also discussed.
- A case study of leveraging SWIPT for the FL service is presented to demonstrate its advantages in terms of enhancing the overall training accuracy with a sustainable energy supply. To this end, we present joint optimization of the SWIPT charging policy and the client-scheduling for FL, which is firstly formulated as a finite horizon dynamic optimization problem and then is solved by the actor-critic-based deep reinforcement learning. Numerical results are presented to validate the performance of the SWIPT-aided FL.

The remainder of this article is organized as follows. We present the key approaches for leveraging SWIPT for FL in Section II. We then discuss the technical challenges in reaping the benefits of SWIPT-empowered FL and their possible solutions in Section III. A case study of the FL empowered by SWIPT is presented in Section IV, and the open research directions are discussed in Section V. We conclude this work in Section VI.

Introducing SWIPT effectively increases the energy capacities of the FL server/clients and thus potentially enhances the performance of FL.

Key Approaches for SWIPT-Enabled FL

Thanks to the dual use of the information carrier for wireless power transfer, SWIPT can be utilized for wireless FL when delivering the global/local models between the FL server and the client devices. Depending on different receivers/sources of the transferred energy, we consider the following important paradigms to exploit SWIPT for FL.

- *(Transferring Power to the FL Clients):* As shown in Fig. 1a, transferring power directly to the FL clients is the most appealing scenario, since the clients (e.g., wireless terminals) are usually energy-constrained due to the limited battery capacities. By performing the dual-role of the global model aggregation and downlink power transfer, the FL server can exploit SWIPT to simultaneously send the global model to the clients and transfer energy to them. Meanwhile, the FL clients can adopt the power-splitting or time-switching approach [13] to receive the global model data and meanwhile harvest energy for supporting its operations, e.g., the local model training and uploading.
- *(Transferring Power to the FL Server in an Infrastructureless Network):* In the scenarios of infrastructure-less networks, the FL server itself might also be energy-constrained. For instance, as shown in Fig. 1b, an unmanned aerial vehicle (UAV) serves as an ad-hoc FL server that coordinates two ground stations as the FL clients for performing the collective surveillance services. In this scenario, the FL clients with a reliable energy supply can adopt SWIPT to actively transfer energy to the FL server when they are uploading the local models wirelessly.
- *(Dedicated Fixed/Mobile Third-Party Chargers for Transferring Power):* Transferring wireless power via a long-distance radio propagation may suffer from a non-negligible attenuation. To address this issue, some dedicated fixed (or mobile) third-party power charging stations can be placed close to the FL clients for enhancing the charging efficiency. As shown in Fig. 1c, a dedicated wireless charging station is placed at the edge of the cell. Being synchronized with the BS, the dedicated charging station can collaborate with the BS (e.g., by forming a non-orthogonal multiple access (NOMA) transmission group with the BS), to transfer wireless energy to the client devices when the BS sends the global model to them.

Introducing SWIPT effectively increases the energy capacities of the FL server/clients and thus potentially enhances the performance of FL. On one hand, SWIPT can prolong the lifetime of the energy-constrained client devices. Thus,

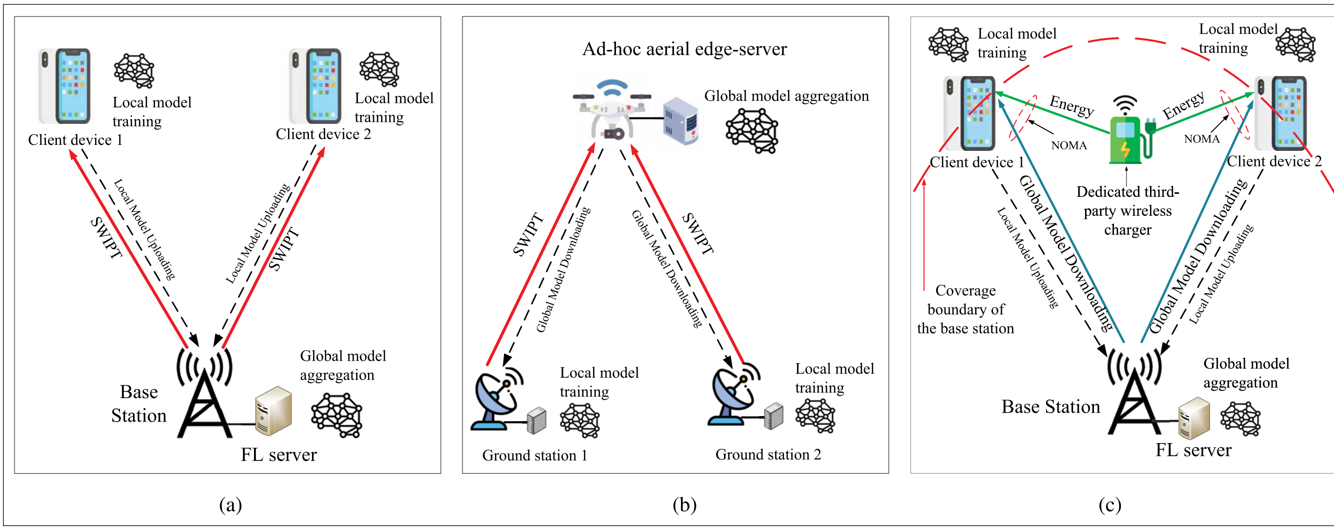

FIGURE 1. Three paradigms of leveraging wireless power transfer. a) Charging for the FL clients. b) Charging for the ad-hoc FL server. c) Dedicated/mobile third-party wireless charger.

more client devices would be available to provide their heterogeneously featured local models, which is beneficial to improve the accuracy of the aggregated global model in FL [9]. On the other hand, the enhanced energy capacities via SWIPT also grant the FL server and clients to achieve a higher flexibility in adapting their operations (e.g., overclocking the CPU frequency for faster computation in training and transmitting with a higher power for sending the models), which in turn helps speed up the global/local models training and transmission. The above advantages of SWIPT are appealing to numerous wireless FL services, especially for the infrastructure-less networks without a reliable on-grid power supply. Some exemplified applications are as follows.

- *(Air-Ground Integrated Networks):* As shown in Fig. 2a,[1] in the integrated air-ground networks, several UAVs are deployed as the edge agents to collect the environmental information and conduct the local training distributively. These locally trained models are then sent back to the ground base station (BS) for aggregation. Considering the UAVs' limited battery capacities, the ground BS can exploit SWIPT to simultaneously send the global model to the UAVs and transfer energy to them for prolonging their lifetimes.
- *(Maritime Networks):* As shown in Fig. 2b, in maritime networks, a group of surface vessels are deployed as the agents to conduct environmental sensing and analysis, while a UAV can be deployed as the FL server for model aggregation. In particular, when being close to the surface vessels, the UAV can be charged by the vessels via SWIPT in parallel with the vessels' uploading of their local models.
- *(IoT Devices):* The limited energy capacity of massive IoT devices has become a bottleneck for performing ML-based tasks and services. Thanks to SWIPT, the indoor wireless access point can play as a charger that transfers wireless power to nearby IoT devices when sending the updated global model to them, as shown in Fig. 2c.

Challenges and Potential Solutions

Despite the benefits of introducing SWIPT for wireless FL, there are several challenging issues when exploiting SWIPT, which are illustrated as follows.

- *(Time-Overhead for SWIPT):* Performing SWITP consumes a certain duration of time-overhead, which, if without a proper control, may adversely impair the FL performance (e.g., a longer latency). For instance, although using a long SWIPT-duration to charge the client devices can enable them to harvest more energy, this directly increases the latency of the single-round FL iteration. To address this issue, it is crucial to investigate a proper management of the time-duration for performing SWIPT such that i) the successful transmission of the global/loal can be guaranteed, and that ii) a sufficient amount of wireless energy can be delivered to accommodate the required operations of the FL server/clients, while taking into account for the time-overhead incurred by performing SWIPT.
- *(Efficiency of Power Transfer):* To improve the accuracy of distributed learning, more clients with heterogeneously featured local data are encouraged to contribute their local models. However, charging the clients might be costly especially when those clients suffer from a poor radio channel condition, leading to a unsatisfactory efficiency in transferring power. Therefore, how to improve the efficiency of SWIPT (e.g., by opportunistically charging those FL clients with favorable channel conditions) while improving the overall FL performance is important.
- *(Intermittency of Harvested Energy):* Due to the open nature of radio channels, the channel condition between the FL server and client devices are time-varying, leading to the fluctuation in the harvested energy via SWIPT. The unstable energy availability adversely impairs the FL performance, e.g.,

[1] In this article, we aim at demonstrating a wide variety of typical yet presentative paradigms of leveraging SWIPT for FL, e.g., those related but with different providers of wireless energy in Figs. 1b and 2a.

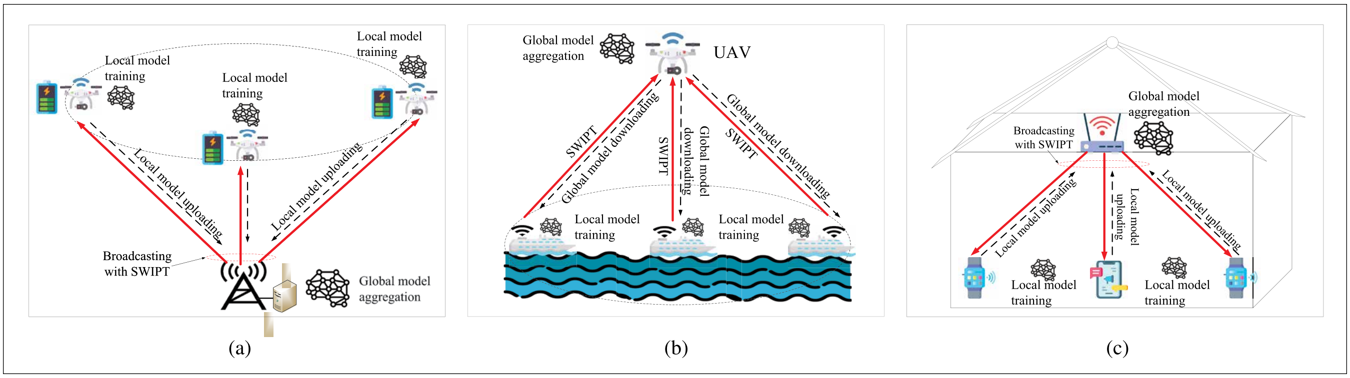

FIGURE 2. Typical applications of leveraging SWIPT for FL. a) Air-ground integrated networks. b) Maritime networks. c) Smart IoT devices.

a temporary degraded local training accuracy due to a shortage of harvested energy at the FL clients. This also leads to a major concern.

- *(Incentive for Transferring Energy):* Exploiting SWIPT to charge the client devices may substantially increase the FL server's energy consumption, which incurs additional economic cost. However, in practice, the FL server and the client devices might be self-interested. Thus, it is crucial to investigate how to motivate the FL server to transfer energy to the client devices in a self-incentive manner.

To address the aforementioned challenges, the following possible solutions are envisioned.

- *(Joint Optimization of SWIPT and FL Configuration):* A proper SWIPT duration should be designed such that the FL clients can collect sufficient energy while receiving the model data successfully. Moreover, to address the time-overhead when invoking SWIPT, a joint optimization of the SWIPT policy and FL iteration is necessary. Specifically, the designed SWIPT policy (i.e., the charging duration and the power/time splitting) should accommodate different clients' needs for local model training (which depends on their settings of CPU frequency and training accuracy) and uploading transmissions (which depend on the clients' transmit-powers, transmit-duration, and other hardware features such as radio frequency front-end). Thus, taking the overall FL performance, e.g., the convergence latency, into consideration, a joint optimization of the SWIPT policy, the FL configuration, and the radio/computing resource allocation can be utilized.
- *(Opportunistic Scheduling and Trajectory Optimization):* Client selection plays an important role in improving the training accuracy while accounting for the limited radio/computing resources at the wireless edge. Opportunistic scheduling of the clients, which jointly considers the time-varying channel conditions as well as different clients' features of local models and remaining energy levels, provides a promising approach to improve the efficiency of wireless power transfer while ensuring the FL performance. In some application scenarios, the FL clients (e.g., UAVs and vehicles) could be moving according to a prescribed trajectory. Exploiting this feature, SWIPT can be invoked when the FL clients and server are close to each other, which thus effectively mitigates the energy transfer loss via radio channel. For instance, for the vehicle networks, the SWIPT can be invoked when the vehicles (as the FL clients) are close to the road side unit (as the FL server) within a certain range. Moreover, to further reap the benefit of short-distance wireless charging, we can optimize the trajectory of a client device such that it can move a favorable location to harvest energy from the FL server with a good efficiency of wireless charging, while accounting for the corresponding cost (e.g., latency and energy consumption) for movement.
- *(Stochastic Optimization for Energy Management):* The time-varying channel conditions may result in some uncertainty in the total harvested energy via SWIPT. To address this issue, the technique of stochastic optimization can be utilized for modeling and optimizing the energy management of the FL server and clients by accounting for the stochastic/unreliable feature of radio channels. Moreover, with the optimal policy produced by the stochastic optimization, the FL clients can further adapt their following operations (e.g., the CPU frequency for their local model training and the transmit power for the model uploading) according to the fluctuated time-varying channel conditions.
- *(Incentive Mechanism for Wireless Power Transfer):* Using SWIPT to provide wireless power to the client devices increases the FL server's own energy consumption cost. A proper design of incentive mechanism is necessitated such that the FL server is willing to provide the wireless power transfer in a self-incentive manner. Specifically, the FL server can ask for the clients' payments to compensate for its own energy consumption cost for wireless charging. Meanwhile, the client devices can also benefit from achieving an improved FL performance while paying for the required charges by the FL server. Several techniques (e.g., the pricing game and contract theory) can be utilized for modeling and analyzing the

above incentive mechanism design, with the goal of achieving the multi-party win-win solution such that the FL server and the client devices can simultaneously benefit from the collaborative power transfer via SWIPT [15].

Case Study of Joint Optimization of SWIPT and Client-Scheduling

We present a case study to demonstrate the advantages of SWIPT-aided FL, by proposing a joint optimization of the SWIPT charging policy and client-scheduling. Specifically, as shown in Fig. 3, a group of client devices (denoted by $\mathcal{I} = \{1, \dots, i, \dots, I\}$) perform local model training under the coordination of a FL server. In the t-th round of the FL iterations, the following operations are performed.

- *(Stage-I):* The FL server exploits SWIPT to simultaneously send the updated global model to all the client devices and transfer energy to them with a transmit power $P_B(t)$ for a duration of T_{SWIPT}. At the client side, each device i adopts the power-splitting of $\beta_i(t)$ to receive the global model and the rest ratio (i.e., $1 - \beta_i(t)$) of the received power for charging its battery, and we assume that each device has a limited battery capacity.
- *(Stage-II):* After being wirelessly charged, each device utilizes its energy supply from its battery to perform the local modeling training and uploading (if it is selected). We adopt the similar model as [8] for measuring each device's energy consumption for its local model training as well as the data transmission and reception. To improve the training efficiency, we consider a dynamic scheduling of the devices to participate in the t-round iteration. Depending on the current system state (which we will specify soon), a subgroup of the devices are selected to conduct the local training and upload the trained models to the FL server. We adopt variable $\alpha_i(t) = 1$ to denote that device i is selected in the t-th round, and $\alpha_i(t) = 0$ otherwise. Notice that supposing $\alpha_i(t) = 1$, device i's available energy after being charged by SWIPT should be sufficient to accommodate its energy consumption for the local training (which depends on its internal CPU-frequency setting) as well as that for uploading the local model to the FL server. Otherwise, device i cannot be selected to perform the local training.
- *(Stage-III):* After the FL server collects the local models from the selected devices at the t-th round iteration, the FL server then performs the model aggregation and evaluates the current value of the loss function.

In general, to minimize the training loss, we prefer to selecting as many client devices as possible to participate the local model training and uploading. However, selecting exceeding numbers of devices in each round of the FL iteration would incur a significant energy consumption of the FL server to charge them via SWIPT. Thus, our objective is to minimize a system-wise cost function that is a weighted sum of the average energy consumption of the FL server and the global training loss after executing T rounds of the global iterations (with the two weights preset to balance the FL training accuracy and the corresponding energy consumption). Specifically,

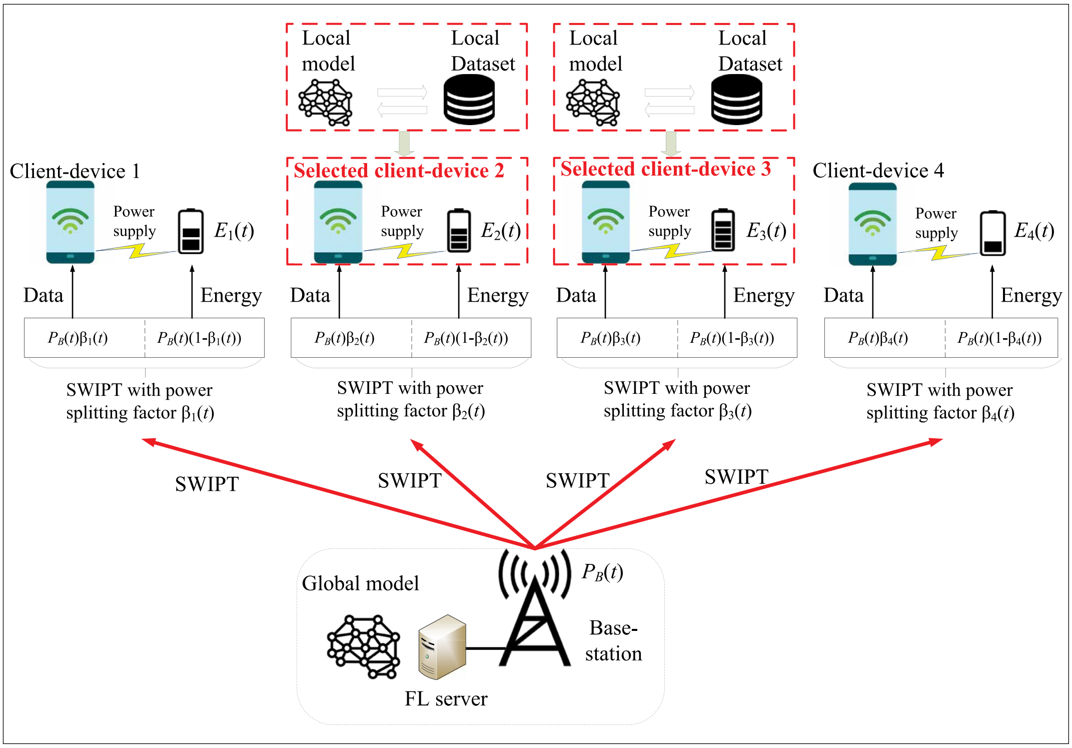

FIGURE 3. A case study of SWIPT-aided FL in which the FL server adopts SWIPT for charging the client devices. As an illustrative example, device 2 and device 3 are selected to perform local model training and uploading at the t-th round of the FL iteration.

in each round of FL iteration, the FL server's energy consumption includes two parts, namely, i) its energy consumption for performing SWIPT and ii) its energy consumption to aggregate the local models from the FL clients. In particular, it is noticed that the FL server's energy consumption for SWIPT also covers all FL clients' consequent energy usages, since the clients harvest energy from SWIPT and further use the harvested energy to perform their respective local modeling training and transmissions. To minimize the system-wise cost, we dynamically optimize the FL server's transmit-power $P_B(t)$, each device's power-splitting $\beta_i(t)$ for receiving data and harvesting energy, and the selection of the devices $\{\alpha_i(t)\}$ for performing local training in each round of the FL iterations. The above joint optimization problem can be regarded as a finite horizon dynamic programming problem. Specifically, at the t-th round iteration, we consider the system state $\mathbf{S}(t)$ comprised of (i) the current channel conditions between the FL server and the client devices, (ii) each device's current battery status, and (iii) the current value of the FL training loss. Meanwhile, we set the action profile $\mathbf{A}(t)$ at the t-th round iteration comprised of the FL server's transmit power $P_B(t)$ for SWIPT, the scheduling of the devices $\{\alpha_i(t)\}_{i\in\mathcal{I}}$ to perform the local training at the t-th round and their power-splitting ratios $\{\beta_i(t)\}$. The essence of our problem is to find an optimal mapping from the system state $\mathbf{S}(t)$ to the action profile $\mathbf{A}(t)$, i.e., the optimal SWIPT policy and the client-scheduling across the iteration horizon. This problem, however, is challenging to solve, since we need to account for a three-folded system state. Moreover, the action space is also complicated, since it includes both the continuous decision-variables (i.e., the FL server's transmit-power and each device's power-splitting in performing SWIPT) as well as the binary decision-variable (i.e., the selection of the client devices in participating in the different rounds of the global iterations). As a result, conventional algorithms are not applicable to solve our problem in the case study. To address this issue, we exploit the capacity of deep reinforcement learning (DRL) based algorithms to realize an efficient decision-making including both the continuous and binary variables. Moreover, we adopt the actor-critic aided DRL (AC-DRL) algorithm, since it can effectively improve the robustness of sample training by avoiding the potential instable training, which thus enables a more efficient and stable convergence of training process compared to the value-based DRL.

To evaluate the performance of our proposed SWIPT-aided FL, we use the real-world data-set, i.e., Fashion-MNIST. In particular, we test the scenarios of 4, 8, and 12 devices. To reflect the system heterogeneity, the number of training samples on all devices are uniformly distributed from 1,000 to 3,000. Each device is randomly located within a circular plane with a radius of 300 meters, and the FL server is located at the centre of the plane. The path-loss model is adopted to generate the channel power gains between the FL server and the client devices. At the beginning of each global iteration, the FL server collects the states of all the devices and computes the actions to instruct the training process. Figures 4 and 5 demonstrate the performance of our proposed SWIPT-aided FL in comparison with two benchmark schemes, i.e., the scheme without SWIPT and the scheme with a fixed power-splitting ratio of 0.5 in SWIPT. We set the size of the global/local model as 100 KB, and the batch size for the local training as 10, and the learning decay-rate as 0.996. In addition, we set the power charging efficiency as 0.8 in SWIPT.

As shown in the left-subplot of Fig. 4, our design of SWIPT-aided wireless FL can effectively reduce the overall system cost in comparison with the other two benchmark schemes. For instance, let us take the case of 4-clients in the left-subplot of Fig. 4 as an example, our proposed scheme can reduce the system cost by 52.89% against the scheme without SWIPT. Such an advantage essentially stems from that SWIPT can increase the devices' lifetimes via wireless charging. As a result, more devices are able to participate in the FL and contribute their local models, which can effectively increase the training accuracy. This point is validated by the right-subplot in Fig. 4, in which the Y-axis denotes the training accuracy (i.e., the tested accuracy of the achieved global model). As shown in this subplot, by using SWIPT, the training accuracy can be effectively improved in comparison with the benchmark result without using SWIPT. In contrast, the FL training accuracy

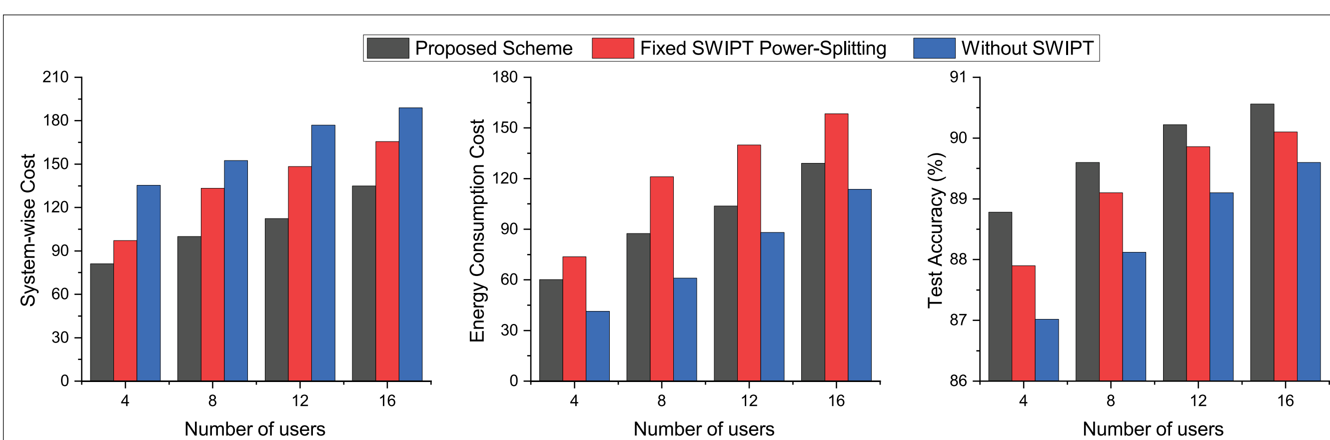

FIGURE 4. Advantages of SWIPT-aided FL compared to two benchmark schemes: system-wise cost, energy consumption cost, and training accuracy.

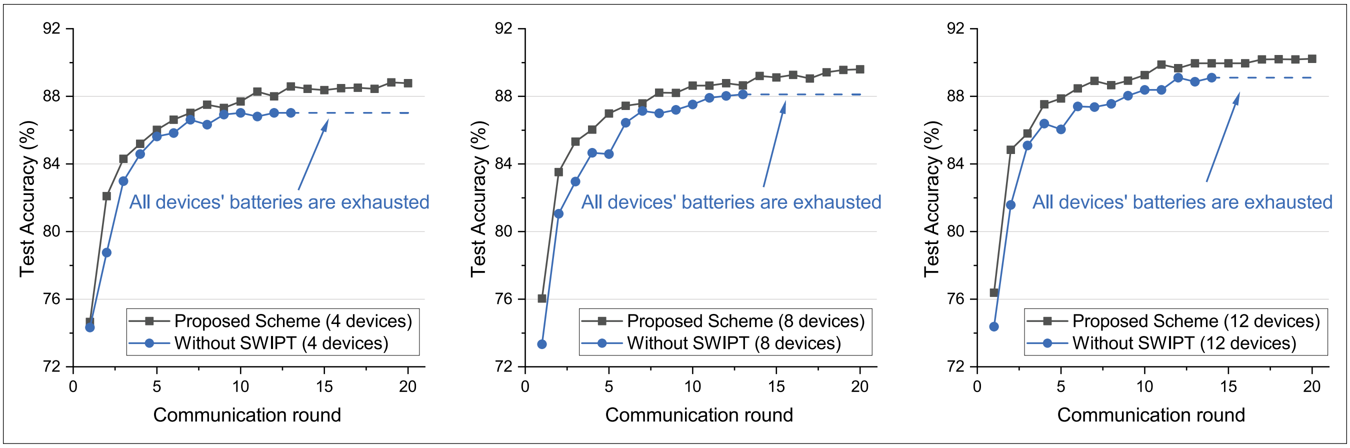

FIGURE 5. Advantages of using SWIPT to provide a sustainable energy supply.

is degraded without using SWIPT, since the client devices quickly exhaust the energy stored at their batteries. Nevertheless, to achieve a more accurate training, it is reasonable to observe from the middle-subplot in Fig. 4 that our scheme consumes a larger energy consumption compared to the scheme without using SWIPT, since we exploit SWIPT to provide the client devices with a sustainable energy supply with which the selected devices can contribute their locally trained models for aggregation.

Figure 5 further demonstrates a detailed comparison between our SWIPT-aided FL and the benchmark scheme without SWIPT in terms of the convergence process of the testing accuracy. It can be observed from the three subplots in Fig. 5 (for different numbers of the client devices), without SWIPT, the testing accuracy is saturated and cannot be improved any further after around thirteen rounds of iterations, since all the devices' batteries are exhausted. In contrast, leveraging SWIPT can provide the client devices with a sustainable energy supply, with which the selected devices can always contribute their locally trained models for aggregation. Thus, the proposed SWIPT-empowered scheme can improve the training accuracy for all the test cases, compared to the benchmark scheme without SWIPT.

Open Research Directions

There are several open directions to further explore when integrating SWIPT with wireless FL services. The details are illustrated as follows.

- *(Intelligent Reflection Surface for Customizing the Radio Channels):* The performance of SWIPT is governed by the channel condition. By using the recent advanced metasurfaces with controllable reflection units, the intelligent reflection surface (IRS) provides an effective approach to customize the wireless channel between the FL server and the clients, which thus improves the performance of power transfer and the model transmission. Although the deployment of IRS introduces a customized strong path, it may also incur co-channel interference among the FL clients and a non-negligible overhead for signal processing. Thus, on one hand, joint optimization of the IRS configuration and the FL operation is necessitated to realize the benefits of exploiting IRS. On the other hand, the balance between achieving the benefit of IRS as well as addressing the consequent complexity in signal processing requires a deep investigation, e.g., a proper setting of the number of reflection elements used by the reflection surface.
- *(Millimeter-Wave for SWIPT-Empowered FL):* Leveraging the ultra-high frequency bands such as millimeter-wave (mmWave) has been regarded as a promising approach for relieving the spectrum congestion in B5G/6G networks. Thanks to the vastly available spectrums, exploiting mmWave bands can enable both an ultra-high throughput for delivering the global/local model data as well as a high-volume power transfer. Nevertheless, mmWave signals are highly directional and susceptible to blockages. Thus, it is challenging to investigate how to achieve the benefits of SWIPT-empowered FL via mmWave bands while accounting for the features of mmWave transmissions.
- *(Multi-Server FL With Hierarchical Structure):* To avoid the congestion at the single FL server for the global model aggregation, the paradigm of hierarchical FL has been envisioned in which several FL servers are deployed and the clients can flexibly select one of the nearby FL servers to upload their respective local models for aggregation. Thus, the association between the FL servers and client devices becomes a critical problem. Moreover, how different FL servers provide efficient wireless power transfer to the properly selected client devices (while sending the global models) requires more investigations.
- *(Age of Information Aware for Client-Scheduling):* Due to the limited computing and communication resources at the FL client devices, training DL/ML model in a distributed manner may introduce latency, which degrades of the timeliness of the services. As a quantitative metric for measuring the freshness of the information, the age of information (AoI) can be leveraged for wireless FL to enhance the freshness of the distributed training. Thus, it is an open direction about how to jointly exploit SWIPT and AoI to achieve fresh FL performance,

e.g., the FL server can use SWIPT to actively transfer more energy to some client devices with critical local models and large AoI such that those devices can speed up their local model training.

- *(Multi-Agent Distributed Optimization):* Various recent studies about the performance optimization of wireless FL assume a centralized optimization approach. Nevertheless, in practical wireless FL services, the FL server and each client device may need to individually optimize their own decisions. This problem becomes even more complicated when the FL server adopts SWIPT to empower the client devices, in which the FL server's wireless charging policy naturally couples with the clients' decisions. Thus, it is challenging to address such a coupling issue due to introducing SWIPT and achieve the distributed decision making of the FL server and client devices. In particular, the recent advanced multi-agent distributed optimization via deep learning serves as a viable solution to address this challenge.

Conclusion

In this article, we have proposed the framework of SWIP-empowered FL that can provide over-the-air wireless power transfer between the FL server and clients in parallel with the transmission of global/local models, which effectively improves the sustainability and performance of wireless FL. We have presented the key approaches of leveraging SWIPT for FL with their advantages illustrated. We then have discussed the major challenges in reaping the benefits of SWIPT for FL and provided the corresponding potential solutions. An illustrative case study of the SWIPT-aided FL is presented to validate the advantage of exploiting SWIPT for improving the accuracy of FL training. We finally have presented several open research directions in the SWIPT-empowered FL with their corresponding research problems discussed.

Acknowledgment

This work was supported in part by FDCT 0162/2019/A3, in part by FDCT-MOST 0066/2019/AMJ, in part by the National Research Foundation, Singapore, and Infocomm Media Development Authority under its Future Communications Research and Development Programme, and in part by the SUTD Growth Plan Grant for AI. The work of Derrick Wing Kwan Ng was supported in part by the UNSW Digital Grid Futures Institute, UNSW, Sydney, under a cross-disciplinary fund scheme, and in part by the Australian Research Council's Discovery Early Career Researcher Award under Grant DE170100137.

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