A Survey on Device Scheduling in Over-the-air Computation-Enabled Federated Learning

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***Abstract*—In this paper, we provide a survey on device scheduling strategies for over-the-air computation (AirComp)-enabled federated learning (FL). Due to the emergence of 6G networks, the combination of FL and AirComp offers significant benefits, especially in terms of spectral and energy efficiency. However, effective device scheduling is critical to maximize these benefits, ensuring precise and timely data aggregation. We mention various scheduling algorithms related to device heterogeneity, communication constraints, and network conditions. This survey highlights the impact of optimized scheduling on the performance and scalability of FL systems as well as aims to guide future research and development in enhancing federated learning with AirComp.**

***Index Terms*—Over-the-air computation, federated learning, device scheduling, gradient importance, channel distortion.**

I. Introduction

The advent of 6G wireless networks promises unprecedented data rates, ultra-low latency, and massive connectivity, pushing the boundaries of current communication technologies. To fully harness the potential of 6G, innovative approaches to data processing and transmission are required. Over-the-air computation (AirComp) is emerging as a critical technology to meet these demands, enabling simultaneous data aggregation and processing directly in the air [1]. This method offers significant benefits such as latency reduction, energy efficiency, and spectral efficiency, making AirComp an efficient wireless communication technique for fields such as the Internet of Things (IoT), sensor networks, and distributed machine learning. Furthermore, the utilization of wireless channels as a computational entity addresses the growing demand for data processing in environments with a large number of interconnected devices.

Federated learning (FL) is a decentralized machine learning (ML) technique that allows collaborative model training without exchanging raw data from the devices [2]. It enables the edge devices to train the model locally and send the gradient updates to the main server, which aggregates all the updates from the devices to generate a global model. This approach reduces the communication overhead, preserves the users' data privacy, and minimizes latency and power consumption. The combination of AirComp with FL enables the latter to enhance its communication efficiency and reduce the latency energy consumption, as AirComp can allow the server to send the local updates simultaneously [3]. This integration is beneficial for IoT networks and mobile edge computing, where the efficient use of resources such as bandwidth and energy is crucial.

One of the critical aspects of AirComp-enabled FL is to have effective device scheduling [4]. In FL, the performance and convergence rate of the global model largely depend on the timely and efficient involvement of edge devices in the training process. Furthermore, device scheduling becomes even more significant in AirComp-enabled FL, as the simultaneous transmission and aggregation of local updates require a well-coordinated approach to have accurate computations and reduced signal interference. Some of the main factors that optimal device scheduling strategies must account for are device availability, computational capabilities, communication conditions, and energy constraints. We can maximize the efficiency of the overall system process of FL by intelligently allowing the devices to participate in training rounds. Due to the abovementioned reasons, this paper surveys the research on device scheduling in AirComp-enabled FL.

II. Device Scheduling in AirComp-enabled FL

This section briefly introduces and explains the device scheduling techniques being researched in the field of AirComp-assisted FL. The existing algorithms consider several factors such as channel conditions, device energy consumption, and local model parameters.

A. Factors-based Device Scheduling

The [5] introduces a novel probabilistic device scheduling framework that aims to mitigate the impact of channel noise on FL by scheduling devices, considering both communication distortion and the global update variance. The proposed method dynamically adjusts the probability of device participation in each communication round, enhancing the overall learning process's efficiency and effectiveness. Their results show that this approach significantly improves convergence speed and model accuracy compared to traditional deterministic, importance-aware, and channel-aware scheduling methods.

In [6], the authors propose a dynamic device scheduling strategy leveraging Lyapunov optimization to balance device quality and channel conditions. Their device scheduling algorithm also considers channel conditions as well as local updates' importance the factor of energy consumption, and it prioritizes devices based on a defined quality indicator, combining data significance and communication efficiency.

Devices with a quality indicator, named channel inversion-based power control, are selected through a quick sorting algorithm, and their transmit power is adjusted accordingly. This approach aims to optimize the number and quality of devices selected in each training round, effectively resisting channel noise while maximizing training performance. The proposed method reduces computational complexity and enhances the adaptability of FL systems.

The [7] proposes a device scheduling algorithm that schedules the devices based on the alignment coefficient for the aggregation process. This method considers the channel conditions of each device, as the alignment coefficient greatly depends on the channel conditions. Moreover, they improved the learning accuracy by optimizing the training loss considering the constraints of privacy and transmit power. This approach shows it to have improved model convergence and robustness against noise.

In [8], a probabilistic device selection scheme designed to improve the convergence performance of AirComp-asssited FL is presented. This approach determines device selection based on predetermined probabilities and scales local updates accordingly. It optimizes selection probabilities by also jointly considering channel conditions and gradient update importance of devices. Their results show the scheme outperforming baseline methods, achieving faster convergence and better model accuracy.

The authors in [9] propose an energy-and-communication-efficient device scheduling scheme for AirComp-enabled FL in UAV swarms, addressing issues of channel distortion and device selection. The proposed scheme derives the optimality gap to measure the impact of factors such as channel distortion and noise on training performance and formulates an optimization problem to minimize this gap. It schedules the UAVs for each round based on transmission and computation energy consumption. The results demonstrate superior training performance and robustness compared to existing methods.

B. Maximizing the Scheduled Devices

The [10] introduces a relay-assisted large-scale FL framework that leverages AirComp for efficient gradient aggregation. The study formulates a joint device scheduling and power allocation problem that is aimed at maximizing the number of scheduled devices while adhering to power consumption and mean squared error (MSE) constraints. This non-convex optimization problem is transformed into multiple sparse optimization problems, which are then solved using a proposed device scheduling algorithm. Their simulation results significantly outperform benchmark methods, validating the approach's efficiency and effectiveness in enhancing FL performance.

In [11], the authors combine AirComp-enable FL with intelligent reflecting surfaces (IRS) for improved model aggregation. This study optimizes learning performance through a novel IRS-assisted AirComp framework to address the challenge posed by unfavorable wireless propagation channels. It aims to maximize the number of scheduled devices in each communication round while meeting mean-squared error (MSE) requirements through a two-step optimization framework. The simulation results indicate that this approach significantly enhances FL prediction accuracy compared to baseline methods.

III. Conclusion

This survey focuses on the importance of device scheduling in optimizing the performance and scalability of AirComp-enabled FL, particularly in the context of emerging 6G networks. The integration of FL and AirComp offers substantial spectral and energy efficiency benefits, but achieving these requires precise and timely data aggregation through effective device scheduling. We mentioned and briefly explained the ongoing research on device scheduling in the field of AirComp-enabled FL. This survey aims to guide future research and development, promoting advancements in FL with AirComp for improved efficiency and performance.

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