Guest Editorial Distributed Signal Processing for Edge Learning in B5G IoT Networks

I. Introduction

EDGE learning (EL) is a promising technology for implementing artificial intelligence (AI) algorithms at edge devices over wireless networks. With the explosive growth in global data traffic, the number of edge devices such as mobile edge computing (MEC), satellite networks, and the Internet-of-things (IoT) devices increase rapidly. Machine learning (ML) techniques, including deep learning (DL), federated learning (FL), and reinforcement learning (RL), are effective approaches to improve the performance and efficiency of edge networks. Traditionally, the AI model in communication systems is trained on a centralized cloud server, which may suffer from the problem of large computational complexity and heavy signaling overhead. Since EL deploys computation-intensive model training at the network edge, highly-distributed real-time data generated by edge devices can be accessed rapidly to accelerate AI training. However, edge devices with limited computational and storage resources lead to new challenges in resource allocation. Other open challenges include data privacy protection and communication latency control. A detailed introduction to distributed EL is given in paper [A1], entitled "*Edge Learning for B5G Networks with Distributed Signal Processing: Semantic Communication, Edge Computing, and Wireless Sensing*," which provides a comprehensive overview of practical distributed EL techniques and their interplay with advanced wireless communication optimization designs.

This special issue (SI) of the IEEE Journal of Selected Topics in Signal Processing aims to provide an overview of the latest advances in various edge networks. In this SI, a total of 52 papers were submitted and 19 of them were accepted. The papers introduced in this SI cover multiple topics, including distributed optimization in edge networks, resource allocation and FL, framework design for EL, and ML in miscellaneous communication applications. In the following, we briefly introduce these papers.

II. Distributed Optimization in Edge Networks

There are seven papers that focus on distributed optimization in edge computing, FL, and satellite networks.

The paper [A2], entitled "*Decentralized DNN Task Partitioning and Offloading Control in MEC Systems with Energy Harvesting Devices*," investigates a decentralized deep neural networks (DNN) task partitioning and offloading control problem for MEC systems with multiple energy harvesting devices. A new Lyapunov function is proposed to optimize the strategy of sequential DNN inference task offloading, taking into account stochastic arrival of both task and energy over an infinite time horizon. By leveraging the Lyapunov drift decomposition and parametric online learning, each optimization subproblem is solved in a decentralized manner for a single wireless device. Simulation results demonstrate its performance gain over various baselines.

The paper [A3], entitled "*Online Edge Learning Offloading and Resource Management for UAV-Assisted MEC Secure Communications*," investigates a UAV-assisted MEC secure communication system. In this paper, an online EL offloading scheme for UAV-assisted MEC secure communications is proposed, which improves the secure computing performance. Moreover, the problem of information security is considered since the offloading information of terminal users may be eavesdropped due to the light-of-sight characteristic of the UAV channels. Simulation results show that the proposed scheme achieves better computing performance and enhances the stability and security compared to the benchmarks.

The paper [A4], entitled "*Mobility-Aware Cooperative Caching in Vehicular Edge Computing Based on Asynchronous Federated and Deep Reinforcement Learning*," proposes a cooperative caching scheme in vehicular edge computing (VEC). The paper first points out that traditional FL methods in VEC rarely considered mobility of vehicles, causing low accuracy of the global model. In addition, the cache capacity of the local roadside unit is not large enough to cache the predicted popular contents. To solve the above problems, this paper proposes an asynchronous FL algorithm to improve the global model accuracy and designs a deep RL algorithm to optimize the cooperative caching method.

The paper [A5], entitled "*Knowledge Selection and Local Updating Optimization for Federated Knowledge Distillation with Heterogeneous Models*," proposes a predicted logits selection (PLS) to improve the convergence performance of local models. The paper first constructs the optimization problem of privileged knowledge selection, and designs an effective iterative algorithm to solve this optimization problem. Then, a model-selection based federated knowledge distillation (MS-FKD) method is proposed to clarify the influence of misleading privileged knowledge on the target local model. Simulation results verify that the proposed method optimizes the knowledge

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aggregation ability between heterogeneous local models and improves the performance of FKD method.

The paper [A6], entitled "*Federated Learning Under Intermittent Client Availability and Time-Varying Communication Constraints*," presents an unbiased algorithm for resource constrained FL systems to eliminate the negative influence brought by intermittent client availability and time-varying communication. An adaptive client selection strategy is learned without any prior knowledge of the communication constraints or clients' availability models, which is theoretically proven to be asymptotically optimal. Simulation results verify its superiority over existing algorithms for all the tested settings with intermittently available clients and communication constraints.

The paper [A7], entitled "*Distributed Data Offloading in Ultra-dense LEO Satellite Networks: A Stackelberg Mean-Field Game Approach*," solves the data offloading optimization problem in a low earth orbit (LEO) satellite network where ultra-dense LEO satellites provide paid data offloading services to large-scale ground users. The joint optimization of data offloading and pricing is formulated as a Stackelberg mean field game (SMFG). The G-prox primal-dual hybrid gradient (PDHG) algorithm and adjoint algorithm are employed to solve the distributed offloading strategy for users and pricing strategy for satellites, respectively. Simulations demonstrate the convergence and efficiency of the proposed solution.

The paper [A8], entitled "*Distributed and Distribution-Robust Meta Reinforcement Learning (D^2-RMRL) for Data Pre-storing and Routing in Cube Satellite Networks*," designs a data pre-storing and routing strategy optimization problem that maximizes the pre-store hit rate in a cube satellite network. To tackle the dynamic and unpredictable data requests of ground users, the optimization problem is formulated as a decentralized Markov decision process. A distribution-robust meta RL-based algorithm is proposed to design the data pre-storing of satellites and routing from the gateway to satellites. Simulation results indicate that the proposed algorithm enhances convergence speed and training efficiency compared to the baseline algorithms.

III. Resource Allocation and Federated Learning

Three papers in this category deal with the tradeoffs in resource allocation for FL.

The paper [A9], entitled "*Privacy-preserving Intelligent Resource Allocation for Federated Edge Learning in Quantum Internet*," proposes a quantum key distribution (QKD) resource allocation scheme in a quantum-secured federated edge learning (FEL) system. Since the number of FEL workers is unpredictable and the demand for QKD resources to encrypt FEL models is uncertain, the authors formulate a stochastic resource allocation model and utilize the federated RL to allocate limited QKD resources in a privacy-preserving manner. Simulations demonstrate that the proposed scheme achieves a lower deployment cost of QKD resources and enhances the training efficiency of the FEL system.

The paper [A10], entitled "*Toward Ambient Intelligence: Federated Edge Learning with Task-Oriented Sensing, Computation, and Communication Integration*," aims to solve a joint sensing, computation, and communication (SC^2) resource allocation problem that accelerates the convergence of FEL. First, the existence of a threshold value for the sensing transmit power is determined by analyzing the wireless sensing process in human motion recognition. Then, the joint resource allocation problem is addressed by solving two subproblems in sequence, i.e., maximizing the total number of training samples via joint sensing and communication resource allocation, and determining a proper batch size at each round for convergence accelerating via the partition of attained samples. Simulation results indicate that the proposed joint SC^2 resource allocation scheme achieves better FEL performance compared to baseline schemes.

The paper [A11], entitled "*Decentralized Federated Reinforcement Learning for User-Centric Dynamic TFDD Control*," proposes a learning-based dynamic time-frequency division duplexing (D-TFDD) scheme that adaptively allocates the uplink and downlink time-frequency resources of base stations to meet asymmetric and heterogeneous traffic demands while alleviating the inter-cell interference. The authors formulate the dynamic resource allocation problem as a decentralized partially observable Markov decision process and propose a decentralized federated RL framework to jointly optimize the D-TFDD control without resorting to global states. Simulation results demonstrate the superiority of the proposed algorithm to benchmark algorithms in terms of sum rate.

IV. Framework Design for Edge Learning

Five papers in this section consider new frameworks for EL and FL.

The paper [A12], entitled "*FedBKD: Heterogenous Federated Learning via Bidirectional Knowledge Distillation for Modulation Classification in IoT-Edge System*," studies the model heterogeneity and data deviation in IoT systems. The authors propose a heterogenous FL framework with bidirectional knowledge distillation to address the current heterogeneity challenge. The authors also successfully implement the proposed FL framework in a modulation classification task and simulation results show the effectiveness of the proposed method.

The paper [A13], entitled "*Federated Learning Using Three-Operator ADMM*," proposes a communication-efficient FL framework, called FedTOP-ADMM, that leverages the data on the edge server to train a global model. Specifically, the authors extend the three-operator alternating direction method of multipliers (ADMM) to learn the global model in FL systems utilizing both data on the edge server and data sets on users. Simulations indicate that the proposed FedTOP-ADMM framework significantly improves communication efficiency compared to common FL algorithms that only utilize the user-side data sets.

The paper [A14], entitled "*Parallel and Memory-Efficient Distributed Edge Learning in B5G IoT Networks*," proposes a parallel and memory-efficient model training by utilizing the computation graph and pebble game. To be specific, the proposed scheme investigates a parallel back-propagation design applied to the operator level, and studies a memory management optimization problem that assigns memory block to IoT nodes for execution of back-propagation computation. The effectiveness of the proposed scheme is evaluated over various real-world DNN architectures.

The paper [A15], entitled "*Communication-Efficient and Model-Heterogeneous Personalized Federated Learning via Clustered Knowledge Transfer*," proposes a clustered codistillation framework, named COMET, which utilizes the data correlation of each edge device. Each edge device uses only an average prediction of other devices with similar data distribution, and prevents edge devices from learning useless knowledge. The COMET allows edge devices to deploy heterogeneous models to adapt to practical scenarios, which overcomes rigid constraints of personalized FL. Moreover, the framework reduces the communication costs and improves the generalization ability of edge device models. Simulation results verify the convergence and generalization of the proposed framework.

In the paper [A16], entitled "*Wireless Federated Learning with Hybrid Local and Centralized Training: A Latency Minimization Design*," a hybrid FL framework comprising centralized and local training is proposed for client-devices with different privacy requirements and computation capabilities. According to rigorous convergence analysis, the client-devices' selections of local training and centralized training, the FL training configurations, and the bandwidth allocations are jointly optimized to minimize the overall training latency. Numerical results demonstrate the effectiveness of the proposed hybrid FL framework, together with optimization algorithms.

V. Machine Learning in Miscellaneous Communication Applications

Three papers apply ML to solve problems in miscellaneous communication, signal processing, and wireless sensing applications.

The paper [A17], entitled "*STAR-RISs Assisted NOMA Networks: A Distributed Learning Approach*," investigates a simultaneous transmitting and reflecting reconfigurable intelligent surfaces (STAR-RIS)-aided downlink nonorthogonal multiple access (NOMA) communication framework that maximizes the average system throughput under the constraints of user QoS requirements. A distributed RL-based approach is proposed to partition the STAR elements and design the tile-based passive beamforming of each STAR-RIS, and the training process is further accelerated via an access-free federated learning (AFFL) model. Simulation results indicate that the tile-based passive beamforming outperforms benchmarks while the STAR-RIS has a large size and the proposed framework effectively reduces the training overhead.

The paper [A18], entitled "*Canny Enhanced High-Resolution Neural Network for Satellite Image based Land Cover Classification and Its Application in Wireless Channel Simulations*," aims to improve the performance of wireless channel semantic segmentation. It proposes a Canny enhanced high-resolution neural network to maintain high-resolution representations and to improve the inter-class distinguishability. It also constructs a new data set for model evaluation. Experiments are conducted on data sets at different granularities, which verifies the superiority of the proposed neural network on the semantic segmentation of wireless channels.

The paper [A19], entitled "*Gaussian Process Upper Confidence Bounds in Distributed Point Target Tracking over Wireless Sensor Networks*," proposes a distributed Gaussian process (DGP) approach for tracking target points with complex behaviors in distributed sensing systems. The paper also analyzes theoretically upper confidence bounds for state estimation error of the proposed approach and proposes a new hybrid Bayesian filtering method to refine the state estimation of the proposed DGP tracking approach.

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Appendix: Related Articles

[A1] W. Xu, Z. Yang, D. W. K. Ng, M. Levorato, Y. C. Eldar, and M. Debbah, "Edge learning for B5G networks with distributed signal processing: Semantic communication, edge computing, and wireless sensing," *IEEE J. Sel. Topics Signal Process.*, vol. 17, no. 1, pp. 9–39, Jan. 2023, doi: 10.48550/arXiv.2206.00422.

[A2] F. Wang, S. Cai, and V. K. N. Lau, "Decentralized DNN task partitioning and offloading control in MEC systems with energy harvesting devices," *IEEE J. Sel. Topics Signal Process.*, vol. 17, no. 1, pp. 173–188, Jan. 2023, doi: 10.1109/JSTSP.2022.3221850.

[A3] Y. Ding, et al., "Online edge learning offloading and resource management for UAV-assisted MEC secure communications," *IEEE J. Sel. Topics Signal Process.*, vol. 17, no. 1, pp. 54–65, Jan. 2023, doi: 10.1109/JSTSP.2022.3222910.

[A4] Q. Wu, Y. Zhao, Q. Fan, P. Fan, J. Wang, and C. Zhang, "Mobility-aware cooperative caching in vehicular edge computing based on asynchronous federated and deep reinforcement learning," *IEEE J. Sel. Topics Signal Process.*, vol. 17, no. 1, pp. 66–81, Jan. 2023, doi: 10.1109/JSTSP.2022.3221271.

[A5] D. Wang, N. Zhang, M. Tao, and X. Chen, "Knowledge selection and local updating optimization for federated knowledge distillation with heterogeneous models," *IEEE J. Sel. Topics Signal Process.*, vol. 17, no. 1, pp. 82–97, Jan. 2023, doi: 10.1109/JSTSP.2022.3223526.

[A6] M. Ribero, H. Vikalo, and G. D. Veciana, "Federated learning under intermittent client availability and time-varying communication constraints," *IEEE J. Sel. Topics Signal Process.*, vol. 17, no. 1, pp. 98–111, Jan. 2023, doi: 10.1109/JSTSP.2022.3224590.

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[A8] Y. Hu, X. Wang, and W. Saad, "Distributed and distribution-robust meta reinforcement learning (D^2-RMRL) for data pre-storing and routing in cube satellite networks," *IEEE J. Sel. Topics Signal Process.*, vol. 17, no. 1, pp. 128–141, Jan. 2023, doi: 10.48550/arXiv.2206.06568.

[A9] M. Xu et al., "Privacy-preserving intelligent resource allocation for federated edge learning in quantum Internet," *IEEE J. Sel. Topics Signal Process.*, vol. 17, no. 1, pp. 142–157, Jan. 2023, doi: 10.1109/JSTSP.2022.3224591.

[A10] P. Liu et al., "Toward ambient intelligence: Federated edge learning with task-oriented sensing, computation, and communication integration," *IEEE J. Sel. Topics Signal Process.*, vol. 17, no. 1, pp. 158–172, Jan. 2023, doi: 10.1109/JSTSP.2022.3226836.

[A11] Z. Yin, Z. Wang, J. Li, M. Ding, W. Chen, and S. Jin, "Decentralized federated reinforcement learning for user-centric dynamic TFDD control," *IEEE J. Sel. Topics Signal Process.*, vol. 17, no. 1, pp. 40–53, Jan. 2023, doi: 10.1109/JSTSP.2022.3221671.

[A12] P. Qi, X. Zhou, Y. Ding, Z. Zhang, S. Zheng, and Z. Li, "FedBKD: Heterogenous federated learning via bidirectional knowledge distillation for modulation classification in IoT-Edge system," *IEEE J. Sel. Topics Signal Process.*, vol. 17, no. 1, pp. 189–204, Jan. 2023, doi: 10.1109/JSTSP.2022.3224597.

[A13] S. Kant, J. M. B. D. Silva Jr., G. Fodor, B. Göransson, M. Bengtsson, and C. Fischione, "Federated learning using three-operator ADMM," *IEEE J. Sel. Topics Signal Process.*, vol. 17, no. 1, pp. 205–221, Jan. 2023, doi: 10.1109/JSTSP.2022.3221681.

[A14] J. Zhao et al., "Parallel and memory-efficient distributed edge learning in B5G IoT networks," *IEEE J. Sel. Topics Signal Process.*, vol. 17, no. 1, pp. 222–233, Jan. 2023, doi: 10.1109/JSTSP.2022.3223759.

[A15] Y. J. Cho, J. Wang, T. Chirvolu, and G. Joshi, "Communication-efficient and model-heterogeneous personalized federated learning via clustered knowledge transfer," *IEEE J. Sel. Topics Signal Process.*, vol. 17, no. 1, pp. 234–247, Jan. 2023.

[A16] N. Huang, M. Dai, Y. Wu, T. Q. S. Quek, and X. S. Shen, "Wireless federated learning with hybrid local and centralized training: A latency minimization design," *IEEE J. Sel. Topics Signal Process.*, vol. 17, no. 1, pp. 248–263, Jan. 2023, doi: 10.1109/JSTSP.2022.3223498.

[A17] R. Zhong, X. Mu, Y. Liu, Y. Chen, J. Zhang, and P. Zhang, "STAR-RISs assisted NOMA networks: A distributed learning approach," *IEEE J. Sel. Topics Signal Process.*, vol. 17, no. 1, pp. 264–278, Jan. 2023, doi: 10.1109/JSTSP.2022.3229567.

[A18] L. Wu et al., "Canny enhanced high-resolution neural network for satellite image based land cover classification and its application in wireless channel simulations," *IEEE J. Sel. Topics Signal Process.*, vol. 17, no. 1, pp. 279–294, Jan. 2023, doi: 10.1109/JSTSP.2022.3222597.

[A19] X. Liu, L. Mihaylova, J. George, and T. Pham, "Gaussian process upper confidence bounds in distributed point target tracking over wireless sensor networks," *IEEE J. Sel. Topics Signal Process.*, vol. 17, no. 1, pp. 295–310, Jan. 2023, doi: 10.1109/JSTSP.2022.3223521.

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