**Research Achievements and Plan**

**I. Research Achievements**

During my graduate program, I have published 7 SCIE papers (5 first author and 2 co-author papers), three first-author papers are published on the top-tier journals in the computer and communication engineering fields (i.e., IEEE Internet of Things Journal, Future Generation Computer Systems). I also have 3 more SCIE papers that are under review process (2 first author and 1 co-author papers). Among my research ideas, four of them are registered as Korean patent and one was transferred to a company. Besides publishing papers, I have attended several international and domestic conferences, one of them is a top-ranked conference on networking research (i.e., IEEE INFOCOM).

I received a scholarship from Brain Korea 21 (BK21) program of Korean Government for my MS and PhD degrees. Based on my research achievements, I was selected to list on “Hall of Fame” among participants of the BK21 program at Chungbuk National University. I also received the “Outstanding Graduate Researcher Award” from the College of Electrical and Computer Engineering and have been nominated for the “Best Thesis Award” from Chungbuk National University.

**II. Research Plan**

Title: **Enabling Decentralized Federated Learning for Industrial Internet of Things**

Objectives:

* To improve the performance of decentralized federated learning approach for IIoT (e.g., fast model convergence, high model accuracy, high robustness)
* To facilitate the deployment of federated learning-based applications in IIoT systems

**1. Introduction**

The industrial internet of things (IIoT) refers to the interconnection of numerous physical devices (sensors, actuators, and machines) and computers applications to enable autonomous and intelligent operations. Especially, applying advanced machine learning ML algorithms to IIoT can enable various smart applications. Federated Learning (FL) is an emerging machine learning technology that allows devices to collaboratively learn a shared prediction model without sending training data to a cloud server. As a result, FL ensures data privacy, reduces communication costs, and improves the learning quality of machine learning applications in IIoT systems. Although the integration of FL and IIoT can result in many benefits, it still faces new challenges needed to address to truly utilize the use of federated learning in IIoT. For example, traditional FL systems use a centric server to aggregate models trained by each device, which can be a bottleneck or single point of failure of the system. Therefore, it is necessary to investigate a fully decentralized FL solution. A decentralized FL approach for IoT devices should be lightweight, offer fast training time, and robustness against malicious attacks while still achieving the high accuracy of the trained model. Another challenge is that IIoT systems may consist of thousands of devices; thus, it is also necessary to develop deployment and resource allocation solutions for scalable federated learning-based applications in IIoT systems.

**2. Previous research**

The FL concept was proposed by Google in 2017 to enable a collaborative machine learning process on local devices without sending data to a centralized server [1]. FedAvg [1] is introduced as the first and state-of-the-art FL algorithm. Many different FL algorithms have been proposed based on FedAvg. For example, a generalization of FedAvg called FedProx [2] is proposed to tackle heterogeneity in FL systems. Most existing FL algorithms follow the centralized approach, which requires an aggregation server in their operation.

Recently, the authors in [3] proposed a fully distributed FL algorithm that leverages Device-to-Device communication for exchanging both model updates and gradients to improve the convergence of machine learning models on IoT devices. However, the experiments in this paper did not conduct with non-IID data. Dealing with non-IID data is considered a key challenge in FL since it can significantly degrade the performance (accuracy) of the FL system.

Regarding the implementation of the FL systems, the authors in [4] proposed a comprehensive FL framework called Flower. Flower allows to execute large-scale FL experiments and it supports richly heterogeneous FL device scenarios. However, to facilitate the use of Flower in real-world FL applications in IIoT systems, it is necessary to combine Flower with a container orchestration tool such as Kubernetes or KubeEdge.

**3. Research Contents**

**a) Robust Decentralized Federated Learning for Multi-hop Wireless Networks**

There is no central aggregation server in a fully decentralized FL system. Initially, each device generates a random parameter (model weights) and trains the local model with its local data. After finishing training, the device sends new parameters to its neighbors through wireless communication. After receiving sufficient parameters from neighbors, each device averages these parameters and re-train the local model with newly averaged parameters. This process is repeated until the local model converges (i.e., reach stable accuracy).

Several optimization techniques can be applied to improve the performance of the local model as:

- Allow each device to dynamically choose hyperparameters (e.g., the number of local epochs, training rate, and batch size) for each training according to the computational resources of each device.

- Apply message compression methods to reduce the communication overhead

**b) Deployment Framework for Federated Learning-Based Applications in IIoT**

The source codes and all dependencies of Federated Learning-based applications are packed as container images. Then, container orchestration tools such as Kubernetes or KubeEdge are utilized to deploy these container images. Finally, resource allocation algorithms are proposed to efficiently deploy FL applications according to the available computational resource of devices in the system and network

**4. Research Timetable**

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| Activities | Month | | | | | | | | | | | | | | | | | | | | | | | |
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
| Literature review |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 1st idea implementation |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Data collection |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Manuscript preparation |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Research presentation |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 2nd idea implementation |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Data collection |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Manuscript preparation |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Research presentation |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Research Extension & Others |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |

**5. References**

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[2] Li, T., Sahu, A. K., Zaheer, M., Sanjabi, M., Talwalkar, A., & Smith, V. (2020). Federated optimization in heterogeneous networks. *Proceedings of Machine Learning and Systems*, 2, 429-450.

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