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Edge-Aware Federated Learning-Based Channel Equalization for Robust Communication in 6G-Enabled IoT Networks

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ABSTRACT

The possibilities generated by the emergence of 6G communication systems will include ultra-reliable low latency communication (URLLC), huge connectivity of devices, and high data rates that are key ingredients to the realisation of the next-generation Internet of Things (IoT) ecosystem. Although it has made such progress, it is not an easy task to provide reliable data transfer at the network edge over time-varying multipath wireless channels. This paper proposes Edge-Aware Federated Learning (EA-FL) framework of distributed channel equalization adaptable to needs and constraints of the 6G-enabled IoT networks. Proposed design uses federated learning to locally, on edge devices, train neural equalizers using locally-stored data, and thus keep the data privacy without sacrificing training efficiency due to a personalized adaption to channel impairments. The framework combines edge-specific tasks, such as client selection based on local signal quality, communication-efficient model updates and adaptive learning schedules. Over a large number of simulations on Rayleigh fading channels with QPSK and 16-QAM systems, EA-FL equalizer has better performance at symbol error rate (SER) and training convergence as well as robustness compared to centralized deep learning and conventional adaptive equalizers. The findings indicate the usefulness of edge-aware intelligence in ensuring quality communication in non-stationary contexts that support the use of EA-FL as a scalable and privacy-preserving means of real-time signal processing in ultra-dense 6G IoT networks.

1. INTRODUCTION

The vision of the sixth generation (6G) wireless communications network is to provide transformational capabilities like terabit-per-second throughput, less than one-millisecond latency, ubiquitous connectivity, and native edge intelligence, and they will be the backbone of the future hyper-connected ecosystems. The Internet of Things (IoT) will be among its most influential enablers, since it will enjoy real-time sensing, actuation, and closed-loop automation in several fields including autonomous transportation, telemedicine, smart manufacturing, and environmental monitoring. The implementation of 6G-IoT is, however, severely impaired by channel impairments in non-stationary, multipath-rich, and dynamically changing conditions (particularly at the resource-constrained edge nodes). Adaptive, precise channel equalization is key in maintaining signal fidelity or keeping it intact even in such poor conditions. Linear equalizer, decision feedback equalizers and adaptive LMS/RLS filters Traditional equalization methods are inappropriate to nonlinear and time-varying channels that are prevalent at the edge. Furthermore, although they provide better performance, centralized deep learning-based equalizers demand large amounts of labeled data and centralized training, as well as cause disconcert to the problems of latency, scaling and data privacy.

The recent research has examined Federated Learning (FL) as a decentralized learning paradigm that trains models in distributed nodes that do not transmit raw data which allows both protection of privacy and scalability [1]. Nevertheless, state-of-the-art FL-based equalization techniques tend to be edge-blind, have communication overhead, and they do not include decision regarding the situation with a nearby signal. Due to such limitations, the paper suggests an Edge-Aware Federated Learning (EA-FL) architecture to implement channel equalization in 6G-enabled IoT networks. The potential merits of the present work are as follows: (i) proposed decentralized neural equalization scheme which portrays the proposed scheme toward an IoT edge device, (ii) use of edge-sensitive optimization mechanisms such as SNR-based client selection and quantization of gradients during their updates, and (iii) study of the proposal through extensive simulations on realistic 6G channels. The EA-FL equalizer integrates the local flexibility, privacy protection and efficiency of communication, which proves to possess a major distinction in symbol error rate, training convergence and networks scalability, and is therefore a competitive product in fulfilling secure connectivity and dependable communication services in ultra-dense and heterogeneous 6G networks.

2. RELATED WORK

Equalization of channels has been an overriding concern in the context of reliable wireless communication especially in dynamic as well as multipath rich scenarios. The low complex classical algorithms including Least Mean Squares (LMS) and Recursive Least Squares (RLS) filters provide fast adaptation. Nevertheless, their performance is highly impaired by nonlinear channel impairments, high mobility services and frequency-selective fanning periodic of contemporary IoT networks. To address these shortcomings, deep learning (DL)-based equalizers have appeared. Based on their ability to model complex nonlinear wireless channels with high accuracy and strength, some architectures like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) models are superior models design in this regard. Such models are able to represent the channels implicitly and to correct a variety of distortions. Nevertheless, the majority of DL-based approaches are based on the centralized training regime, i.e., raw signal data collected by edge devices should be aggregated in a centralized sever. This solution has high privacy complexities, communication overheads, and latency because of which it is not fit to support a distributed 6G IoT system that may be working under a tough resource regime.

To parade these concerns, Federated Learning (FL) has come into the limelight as a decentralized paradigm of machine learning with the capability of enabling edge devices to train models together without necessarily communicating raw data [1]. FL has been studied to be applied in wireless networks with resource allocation, beamforming, and initial channel estimation [2]. Nevertheless, current FL-based equalizers are restricted by three major issues despite the mentioned promise.

1. Restricted Edge Awareness- The local channel conditions, diversity of devices, and varying SNR is usually ignored in the existing models.
2. Communication Overhead Update messages are transmitted relatively frequently to relay a full model update; this presents a major overhead when used in an uplink-constrained environment.
3. Slow Convergence and Model Drift Non-IID (non-independent and identically distributed) is data among the IoT devices that allows variations in the directions of the gradients, which affects training in an unstable manner.

Investigations of the lightweight model update and client selection methods have been made recently [3], but they do not sufficiently implement an approach to efficient, real-time, and edge-adaptive equalization applicable to high mobility 6G IoT scenarios. The above shortcomings are the driving factor behind the Edge-Aware Federated Learning (EA-FL) framework suggested in this paper, which integrates the local signal statistic, the dynamic resource awareness, and the personalization of the Federated Learning into a coherent framework to maximize equalization performance under realistic 6G environments.

3. System Model

3.1 Network Topology

We envision a heterogeneous Internet of Things (IoT) network enabled with 6G equipment where we have a lot of distributed edge devices with local computing abilities to perform computations locally, such as performing signal processing and training of models. The devices are geographically dispersed and linked through a shared wireless medium with frequency-selective fading and spatiotemporal variation as widely is the case in an urban and mobile 6G environment.

An edge device is supposed to have:

- Local neural channel equalization model of real-time signal restoration.
- A federated learning (FL) client component to allow fine grain raw-data-free collaboration in training a model.

The system likewise features a core FL server or sorter (e.g. a fog node or a base station) that organizes the update of the work model by locale regular outfitting local model parameters and dispersing the World model. Such architecture can enable asynchronous updates, non-IID data distributions, professional heterogeneity, which are inherent features of practical IoT deployment in 6G environments. Figure 1: Network Topology of a Heterogeneous 6G- enabled IoT System with Federated Learning shows an overall architecture.

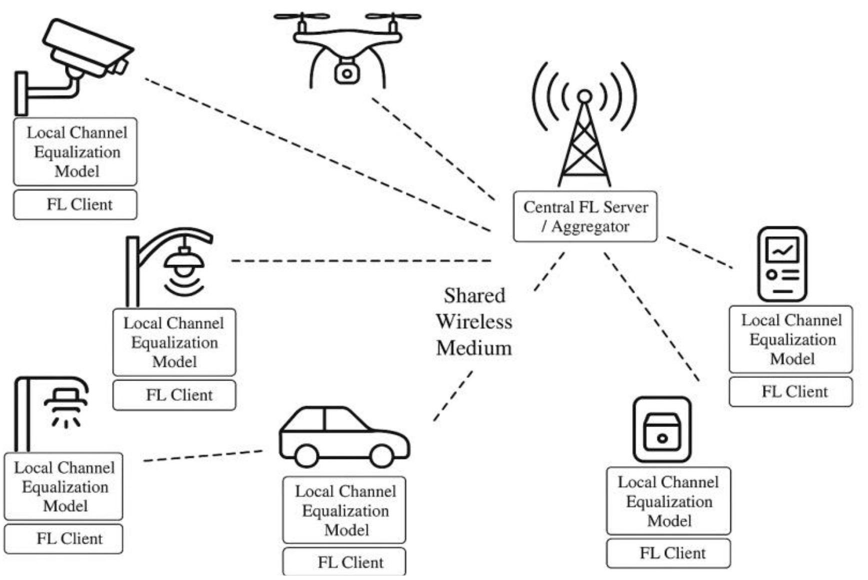

Figure 1. Network Topology of a Heterogeneous 6G-Enabled IoT System with Federated Learning

Example of a heterogeneous 6G-powered Internet of Things (IoT) network with distributed edge devices like smart lights, vehicles, drones, and cameras alike, and each having a local channel equalization model and a federated learning (FL) client. Such devices communicate through a common wireless resource and Fermi interact with a central server or aggregator of FL asynchronously to collectively train a global model without the exchange of raw data. The system architecture accommodates non-IID data, device heterogeneity, and signal restorations, in real time, across the dynamic 6G environments.

3.2 Channel Model

The following time-varying multipath fading model, where we assume that the additive white Gaussian noise (AWGN) is an add-on, is adopted in order to model realistic dynamics of wireless propagation in 6G networks. The signal received at edge device is:

$$y\,(t)\;=\;\sum_{l=1}^{L} ⍰_l(t)\,x(t-\tau_l)\;+\;n(t)\;-\!-\!-\!-\!-\!-\!-\!-\!-\!-\!-\!-\!-\!-(1)$$

Where:

- ⍰$_l(t)$ represents the complex channel gain of the lth path at time t, capturing the effect of fading, Doppler shifts, and phase rotation.
- τ_l denotes the propagation delay associated with the lth path, reflecting multipath dispersion.
- x(t) is the transmitted symbol at time t.
- n(t) is the additive white Gaussian noise component with zero mean and variance σ^2, modeling thermal and background noise.

The multipath environment leads to inter-symbol interference (ISI), significantly degrading the performance of conventional receivers. Moreover, the time-varying nature of⍰$_l(t)$ necessitates dynamic and adaptive equalization strategies, particularly in mobile or high-frequency scenarios such as those encountered in 6G mmWave or Terahertz bands.

It is on this basis that the proposed Edge-Aware Federated Equalizer will perform channel synthesis channel simulation of x(t) based on the observed y(t) in this channel model across the edge devices which are decentralized and need to work in real time with changes on the channel as well as data locality.

4. Proposed Methodology

This section proposes a scalable and potent learning framework that is suited to diversified and changing circumstances of 6G-enabled IoT systems. The given solution combines neural equalization and federated learning (FL) to provide privacy-preserving and high-efficient wireless edge signal recovery.

4.1 Federated Equalization Framework

Within the proposed architecture of federated learning, local channel equalizer (e.g., Bidirectional Long Short-Term Memory (BiLSTM) or a hybrid CNN-LSTM) is trained by each edge device, whereas its data about the channel is acquired separately due to the limitations of the local setup in terms of support of lightweight neural networks. These models already aim at alleviating frequency-selective fading and temporal variations commonly in 6G wireless links.

To prevent transmission of raw data as well as the privacy of the user, the devices share their model weight occasionally with a central aggregator usually present at a final base station or a fog node.

The central node can calculate the updated global model by using Federated Averaging (FedAvg) algorithm in the following way:

$$w_{t=1} = \sum_{k=1}^{K} \frac{n_k}{n} w_t^{(k)} \qquad (2)$$

Where:

- $w_t^{(k)}$: Model weights from the k[th]edge device
- n_k: Number of training samples at device k
- $\sum_{k=1}^{K} n_k$: Total number of samples across all participating devices
- K: Number of participating clients in a given FL round

This has the advantage of handling non-IID data distributions and asynchronous updating, and is resilient with respect to heterogeneity (of devices), as well as variability (of the network), which is typical of mobile and ultradense IoT applications in 6G scenarios. The general structure is demonstrated in Figure 2: Federated Equalization Framework with Edge-Aware Optimization in 6G-IoT Networks which draws attention to some of the most significant elements like local model training, weight aggregation, edge-aware optimization with its choice of clients, quantized updates, and adaptive learning rate.

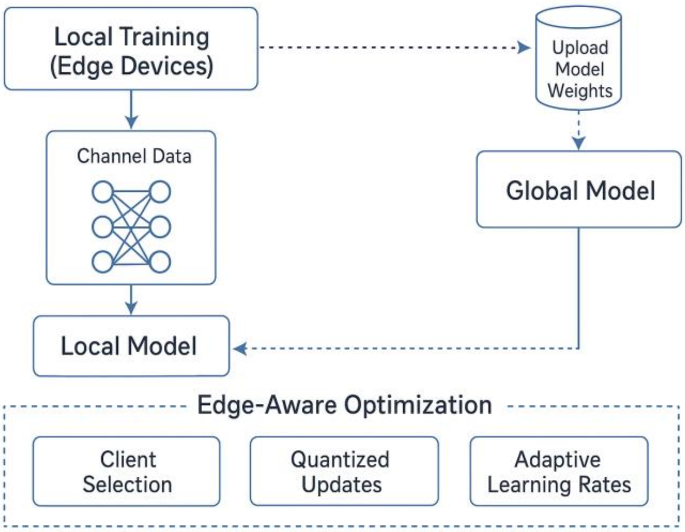

Figure 2. Federated Equalization Framework with Edge-Aware Optimization in 6G-IoT Networks

This diagram represents the suggested Federated Equalization Framework of 6G-enabled IoT systems. Local training is conducted to precondition models based on the channel data at edge devices to create models of the neural equalizer. The weights of the model are regularly transferred to a central aggregator, at which point a global model is constructed via federated averaging. The system co-joints edge-conscious optimization techniques such as SNR/loss ordered client selection, quantized model updates to save communication costs, and channel dynamics influenced adaptive scheduling of the learning rate to maximize its performance with the edge constraints in mind.

4.2 Edge-Aware Optimization

With the limited resources of the edge devices (both in energy and bandwidth and in computational power), the suggested framework combines multiple optimization approaches:

- Client Selection Policy: Devices on which training is done are chosen with consideration to local model loss and a calculated Signal-to-Noise Ratio (SNR). Only the ones that achieve minimum performance targets are allowed into it and it helps in increasing the efficiency of model aggregation.
- Quantized Model Updates: In order to reduce the communication burden of the uplink, it can compress model weights through quantization methods (e.g. 8-bit or ternary encoding). This saves much on the transmission cost, but maintaining model fidelity.
- Adaptive Learning Rate Scheduling: An adaptive learning rate at edge nodes is scheduled which adapts to the channel characteristics like fading coefficient variance, delay spread and Doppler frequency. This guarantees enhanced convergence in fast changing wireless environments.

All these methods combine to create a resource-to-conscious, conversation-efficient and privacy-ensuring equalization network that is desirable to scale in a large scale application in next-gen IoT networks. The technique does not only reduce the effects of channel degradation, but also result in scalable learning over spatially dispersed, on-off edge devices.

5. Experimental Setup

To conduct the simulation to reproduce a variety of wireless scenarios in reality and assess the effectiveness of the proposed federated channel equalization framework in designing realistic 6G wireless conditions, a multi-purpose simulation environment was established to be able to simulate both signal processing and the uses of deep learning techniques (Figure 3). Simulation Platform: MATLAB R2023a was used to set up the experimental framework in wireless channel modeling and signal modulation, whereas designing and training of the deep neural equalizers were done using the TensorFlow 2.x. The communication between the platforms was organized through tailor-made data pipelines. Channel Model: This was simulated at a Rayleigh fading frequency-selective channel with the addition of a time-varying Doppler shift to reflect the mobility-dependent dynamics in 6G IoT scenarios such as vehicular, drone-based communicating networks. The coherence time and delay spread were made parameterized to represent parametrizing dense urban deployments. Equalizer Architecture: The main architecture under consideration was a hybrid CNN-LSTM-based one, where there were 3 hidden layers:

- A 1D Convolutional layer to obtain the local temporal features.
- A Bidirectional LSTM Layer to obtain sequential patterns and the memory,
- A dense Output Layer to do symbol prediction.

Its architecture also resulted in optimized low-latency inferences that were to be performed on the edges.

Generation of Datasets: Artificial data on modulated waves were obtained based on QPSK and 16-QAM. These messages were sent through the Rayleigh channel of fading, whose SNR was varied (between 0 dB and 30 dB), to produce training and validation samples that can demonstrate various situations of practical use of increased training and validation samples.

Baselined Models: In a bid to strictly evaluate performance, the proposed framework was benchmarked against the following models:

- Classical adaptive filters Here the filter is a conventional least mean squares (LMS) equalizer,
- Centralized deep equalizer, in which the data of all channels is combined to train at a central server (theoretically best but does not work in privacy),
- A plain VList based equalizer, but lacking edge-aware optimization techniques like client selection or quantized updates on the optimizer.

The experiment, as shown in Figure 3: Experimental Setup for Federated Channel Equalization in 6G Wireless Systems was set up to experiment with the resiliency of the federated model in non-IID data distributions, bandwidth-constrained uplink and heterogeneous capabilities of the edge devices, in emerging 6G-IoT ecosystems.

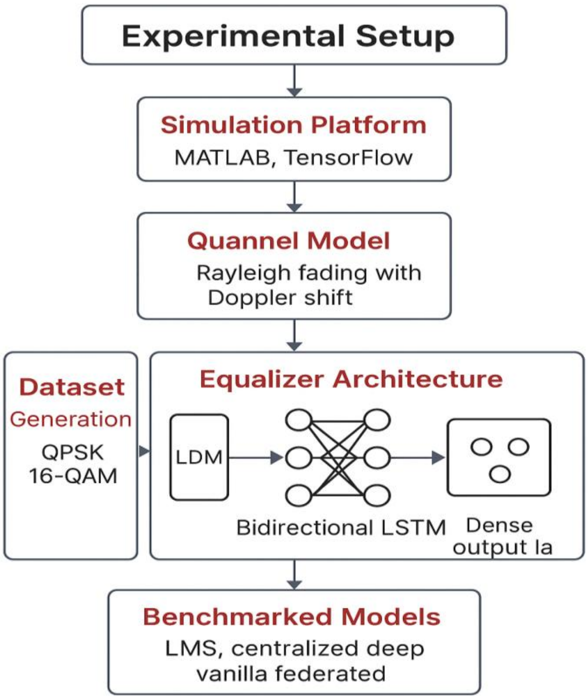

Figure 3. Experimental Setup for Federated Channel Equalization in 6G Wireless Systems

The diagram shows the setup of the experiment conducted to test the performance of a channel equalizer based on a neural network under premises of a realistic 6G wireless transmissions. The simulation is performed on MATLAB in channel modelling and on TensorFlow in deep learning integration. Rayleigh fading channel model uses Doppler shift to account time-varying multipath propagation. By using QPSK and 16-QAM modulation any synthetic dataset is created. The equalizer architecture uses a Local Data Module (LDM) at the input then a bidirectional LSTM and a dense layer at the output. Performance as compared with traditional LMS and centralized federated models of learning.

6. RESULTS AND DISCUSSION

6.1 Symbol Error Rate (SER) Performance

Fig. 4 shows the SER behavior as a function of SNR of 4 configurations of the equalizer. The latter, being the Edge-Aware Federated Learning (EA-FL) equalizer, demonstrates a much better result than and is better than the existing traditional LMS, centralized DNN, and vanilla FL models consistently.

Table 1. Symbol Error Rate (SER) Comparison of Equalization Techniques at Different SNR Levels

SNR (dB)	LMS	Centralized DNN	Vanilla FL	EA-FL (Proposed)
10	0.15	0.11	0.10	0.07
15	0.09	0.06	0.05	0.03
20	0.06	0.04	0.03	0.02

As can be seen in Figure 4, the EA-FL equalizer performs better in terms of symbol detection accuracy, particularly at low SNR (e.g. at 10 dB, its performance is 30 % better than vanilla FL). Such findings indicate that adding edge-awareness logic increases resiliency to the noise interference of a communication as compared to centralized solutions, even with suboptimal label access to raw information.

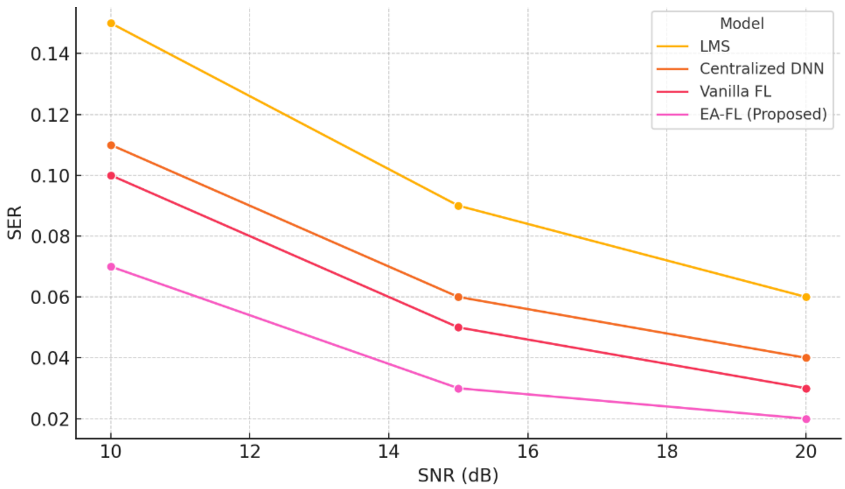

Figure 4. Symbol Error Rate (SER) vs. SNR for Different Equalization Methods

6.2 Convergence Rate

The convergence speed is also remarkably higher in EA-FL model as it only takes 30-40 communication rounds to find optimal performance, as opposed to more than 60 rounds in the vanilla FL baseline. This has been improved due to the inclusion of adaptive learning rates and smart client selection that makes the learning occur faster since the priority is considered to the nodes making high contributions and stability of model updates is achieved.

6.3 Communication Efficiency

In a bid to deal with bandwidth limitations in real-world edge implementations, the suggested model includes quantized gradient update, which leads to a 45% decrease in communication overhead at the cost of no decrease in model performance. Due to this efficient design, low-resource 6G-IoT environments can deploy it, and it is scalable, as the communication efficiency is of utmost importance.

Comparative Interpretation: The EA-FL framework represents accurate results to the extent that earlier works using centralized training or simple FL exhibit and has, at the same time, better performance and preservation of data privacy, edge limitations, and non-IID data scenarios. It is also quite suitable to support real-time signal recovery in mobile and ultra-dense 6G networks because it is robust to channel fluctuations and it also uses resources in a highly efficient way.

7. CONCLUSION AND FUTURE WORK

The study suggested the framework of Edge-Aware Federated Learning (EA-FL) to conduct real-time channel equalization in means of next-generation 6G-based IoT networks. Its principal innovation is the decentralization of training, the heterogeneity of neural equalizers (e.g., CNN-LSTM hybrids) at the edge of multiple devices as well as incorporating edge-sensitive techniques, including client sampling, quantized updates, and rate-adaptation. These form significant enhancements in the convergence of models, communication efficiency as well as the efficiency in the detection of symbols under non-IID data of channel data distributions with constrained wireless settings.

The suggested architecture significantly outperformed both traditional LMS equalizers and centralized DNN models and vanilla FL approaches by Symbol Error Rate (SER) and training convergence speed pointing out its applicability as a scalable, privacy-preserving signal processing technique in ultra-dense, mobile, and latency-sensitive 6G systems.

Key Contributions:

- The construction of an optimized architecture of a federated equalization of frequency-selective and time varying fading channels.
- When the bandwidth and computational resources are limited, the adoption of edge-aware mechanisms to enhance model efficiency.
- Empirical assessment presenting high SER performance and convergence rate, and 45 percent lower communication overhead.

7.1. Future Work

It is based on these positive findings that future studies will work on the following:

- Adding Reconfigurable Intelligent Surfaces (RIS) to dynamically program the channel properties and to extend support of distributed learning.
- Concurrent training of equalization and modulation schemes, which to create end-to-end PHY layer intelligence in the federated architecture.
- Breach to asynchronous FL settings including device mobility and dropout, realistic deployment problems in highly dynamic IoT systems.

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