A Communication-Efficient Protocol for Federated Learning in Energy Storage Systems

Xu Wang, *Student Member, IEEE*, Yuehan Qi, Yuanzhu Chen, *Member, IEEE*, and Octavia A. Dobre, *Fellow, IEEE*

***Abstract*—In recent years, battery-backed energy storage systems have received significant attention due to the proliferation of renewable energy. Monitoring energy storage systems and identifying abnormal batteries is essential for their usability and dependability. Due to the scarcity of anomalous measurements at the early deployment stage of energy storage systems and privacy concerns, we collectively train a global autoencoder to identify anomalous batteries over multiple battery-backed energy storage systems. However, the repetitive model weights exchanges during federated learning induce large communication overhead. To address this issue, this poster presents an efficient communication protocol to reduce the number of bits used to represent each model parameter and thus reduce the transmission delay without sacrificing their values. Experimental results show the effectiveness of the proposed communication protocol.**

***Index Terms*—Energy storage systems, federated learning, IEEE 754 standard, autoencoder**

I. Introduction

Paris Agreement and Global Climate Goals necessitate the massive deployment of low-carbon energy. It is anticipated that renewable capacity will account for about 95% of the increase in worldwide power capacity through 2026 [1]. However, the major drawback in promoting renewable energy is its intermittent nature. The integration of battery-backed energy storage systems (BESSs) with sustainable energy is essential because it reduces the fluctuation of available power. Consequently, it is crucial to monitor the functionality of BESSs.

Due to the lack of available anomalous measurements and privacy constraints, we train a global autoencoder in a federated way to detect anomalous batteries. However, training a global autoencoder in a federated manner for BESSs is quite challenging for two reasons. First, BESSs are often located in remote areas with limited network connectivity. Second, BESSs are often equipped with resource-limited computers. Therefore, the communication overhead constitutes a major bottleneck for federated learning-empowered BESSs. We are encouraged to reduce the size of autoencoders.

To address this challenge, we propose a communication-efficient protocol to reduce the transmission delay. Based on the observation that the absolute value of weights is fixed within a specific range, we modify the IEEE 754 standard [2] with 5 exponent bits and 6 fraction bits, generating a 1.5 bytes representation. It is noted that the proposed communication protocol can represent each weight exactly, while the traditional quantization methods suffer from quantization errors due to the round operation [3].

Xu Wang, Yuehan Qi, and Yuanzhu Chen are with the School of Computing, Queen's University, Kingston, ON K7L3N6 Canada. (Emails: {xu.wang, 18yq36, yuanzhu.chen}@queensu.ca).

Octavia A. Dobre is with the Faculty of Engineering and Applied Science, Memorial University of Newfoundland, St. John's, NL A1C5S7 Canada (Email: odobre@mun.ca).

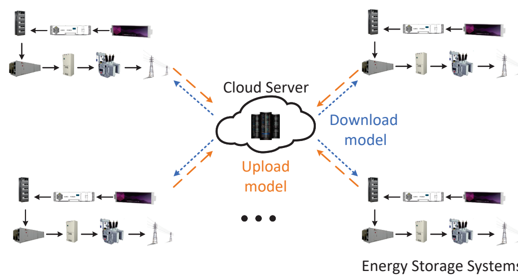

Fig. 1. Federated learning-empowered energy storage systems.

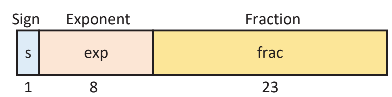

Fig. 2. IEEE 754 standard single-precision floating-point format.

II. Background

A. Federated Learning-Empowered Battery-Backed Energy Storage Systems

Fig. 1 depicts federated learning-empowered BESSs to detect anomalous batteries. Particularly, BESSs receive an initial autoencoder from the cloud server. BESSs use local normal measurements to adjust the received autoencoders and then have enhanced gradients and autoencoders. BESSs then transmit these gradients back to the cloud server, which adjusts the global autoencoder based on these parameters. After the global autoencoder has been fine-tuned, BESSs download the updated autoencoder for the next round of training. After multiple training rounds, the global autoencoder could discriminate normal measurements and locate anomalous batteries with the use of threshold on the reconstruction error.

B. Single-Precision Floating-Point Format in IEEE 754

In BESSs, the weights of autoencoders are stored in the single-precision floating-point format. As shown in Fig. 2, the bit representation of a floating-point number consists of three parts in the single-precision. First, the single sign bit s directly represents the sign of the floating-point. Second, the 8 bits exponent field represents the exponent E. Third, the 23 bits

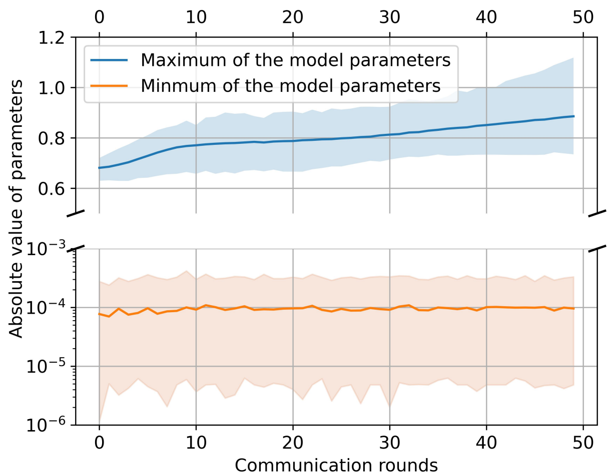

Fig. 3. Evolution of model parameters.

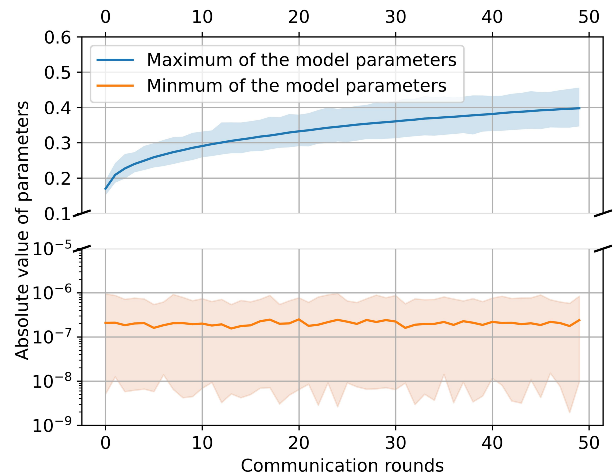

Fig. 4. Evolution of model parameters over MNIST dataset.

fraction represents the significand M. As a result, they generate a 32 bits representation.

III. Proposed Protocol

In order to reduce the model size and mitigate the transmission delay between BESSs and the cloud server, we design an efficient communication protocol to reduce the number of bits required to represent each model parameter during communication.

We cooperate with KORE Power. Inc. and collect measurements from five BESSs. Each energy storage system provides 1000 normal measurements with 52 dimensions. Besides, we have a test set of 2000 measurements, where half of them are anomalous measurements. The autoencoder has 2054 model weights, in which the encoder consists of two hidden layers of 16 and 8 neurons, respectively. Fig. 3 illustrates the evolution of model weights over multiple real-world experiments for 50 communication rounds. The upper bound of the shadow refers to the 97.5 percentile, and the lower bound of the shadow indicates the 2.5 percentile. The line in the middle is the mean value of model parameters. We observe that the absolute value of the model parameters in federated learning for energy storage systems is greater than or equal to 10^{-6}, and less than 10^{1}. For single-precision floating-point format, the smallest positive value it can represent is around 1.4×10^{-45}, and the largest normalized value it can represent is around 3.4×10^{38}. Apparently, transmitting model weights in single-precision floating-point format between BESSs and the cloud server is inefficient and generates huge transmission delay.

In order to improve communication efficiency and reduce transmission delay, we propose to store weights with more compact formats with 5 exponent bits and 6 fraction bits, generating a 1.5 bytes representation. It is noted that for the proposed communication protocol, the smallest positive value it can represent is around 9.5×10^{-7}, and the largest normalized value it can represent is around 6.6×10^{4}. In addition, the header fileds of the proposed communication protocol include the number of bits used for a single floating point number and exponent, as well as a scaling exponent such that the proposed protocol is maximally flexible.

IV. Experiments

The proposed communication protocol can be easily extended to other applications. We experiment with the proposed communication protocol on the MNIST dataset. Fig. 3 illustrates the evolution of model weights over multiple experiments for 50 communication rounds in image recognition. As shown in Fig. 3, the absolute value of the model parameters in federated learning for energy storage systems is greater than 10^{-9} and less than 10^{1}. With 5 exponent bits, 6 fraction bits, and scaling exponent 9, the smallest positive value the proposed protocol can represent is around 1.9×10^{-9}, and the largest normalized value it can represent is around 128.

V. Concluding Remarks

This poster presents a communication-efficient protocol for federated learning in energy storage systems. Instead of using 32-bit floating point format to represent model parameters, we store weights with more compact formats. By reducing the number of bits used to represent model parameters, the size of model parameters can be significantly reduced, resulting in decreased transmission delay. The communication bottleneck is not unique to energy storage systems. We can easily extend our work to other applications. Simulation results validate the effectiveness of the proposed framework in image recognition.

References

[1] I. E. Agency. (2022, Jun.) World Energy Investment 2022. [Online]. Available: https://iea.blob.core.windows.net/assets/b0beda65-8a1d-46ae-87a2-f95947ec2714/WorldEnergyInvestment2022.pdf

[2] "IEEE standard for floating-point arithmetic," *IEEE Std 754-2019 (Revision of IEEE 754-2008)*, pp. 1–84, 2019.

[3] S. Gupta, A. Agrawal, K. Gopalakrishnan, and P. Narayanan, "Deep Learning with Limited Numerical Precision," in *Proc. 32nd Int. Conf. Machine Learning. (ICML)*, vol. 37, Lille, France, Jul. 2015, pp. 1737–1746.