Federated Learning for Intelligent Resources Allocation in Internet of Things

Mahmoud Ismail*[1], Shereen Zaki [2]

[1,2] Faculty of computers and Informatics, Zagazig University, Zagazig, 44519, Egypt
Emails: mmsabe@zu.edu.eg; SZSoliman@fci.zu.edu.eg
*Correspondence: mmsabe@zu.edu.eg

Abstract

By using federated learning (FL), multiple Internet-of-Things (IoT) devices can construct a shared learning model without sending raw data to a centralized server. While FL has come a long way, it still has a ways to go. Issues such as heterogeneous user equipment (UEs) and data that is not independently and uniformly distributed are still obstacles. Facilitating a numerous UEs to participate in the learning in each cycle poses a possible problem of the huge communication budget. A weighted adjoining factor is presented to the localized gradient descent, generalizing the present FedAvg to solve these concerns. At the start of each global round, the proposed FL method randomly selects a fraction of the UEs to perform stochastic gradient descent in parallel. Then, we utilize the suggested FL method in cellular IoT to reduce either total power usage or execution duration of FL, in which a straightforward but effective path-following method is constructed for its explanations. At last, obtained simulations on poorly balanced data are presented to show that the presented FL algorithm is superior to FedAvg in terms of performance with respect to fast convergence. Moreover, they show that the suggested algorithm needs significantly less time and energy to train than the FL algorithm does when users contribute heavily to the learning process. These findings provide strong support for the suggested FL algorithm as a potential paradigm change for training mobile IoT networks with limited bandwidth.

Keywords: Internet of Things; Cellular Network; Mobile Edge Computing; Federated Learning; Resource Allocation;

1. Introduction

IoT (Internet of Things) refers to the network of physical devices, vehicles, appliances, and other items embedded with sensors, software, and connectivity that enable these objects to connect and exchange data. As a result of this connectivity, IoT devices generate and transmit large volumes of data. Dealing with the large volume of data generated by IoT devices can be a challenge. However, this data can be very valuable as it can provide insights into customer behavior, operational efficiency, and product performance, among other things. To handle the large volume of data generated by IoT devices, businesses and organizations can use various tools and technologies such as cloud computing, big data analytics, and machine learning. These technologies can help in processing and analyzing large volumes of data to extract valuable insights, such as identifying patterns, trends, and anomalies. Moreover, edge computing can also be used in IoT to process data closer to the source, which can reduce the amount of data that needs to be transmitted to the cloud and improve response time.

Cellular IoT development has advanced rapidly due to wireless communication and computing advances [1]. Cell phones, wearable gear, and mobile apps have started appearing in cellular IoT networks. Cellular

Doi: https://doi.org/10.54216/JISIoT.070106
Received: March 26, 2022 Accepted: October 21, 2022

IoT networks are used in clubs, factories, navigation systems, smart cities, and medicine. Despite the rapid rise of cellular IoT infrastructure, there are still substantial architecture challenges. Creating an effective and adaptive cellular IoT management system is a major task. This will reduce energy consumption, increase application count, and make the system viable for future developments. Mobile devices in cellular IoT networks face substantial challenges in computational power, computational space, battery life, and other areas. MCC lets mobile UEs send data to the cloud for processing. MCC has greatly increased mobile UE capacity in recent years. MCC may accelerate mobile UE adoption and reduce energy use, but it may also increase communication costs. MEC transmits cloud data to nearby computational access points, unlike MCC. Hence, MEC can support smart factories, sustainable cities, sports matches, and automotive networks in cellular IoT networks. Due to rapid technological innovation and public awareness of how to better protect themselves, people are paying more attention to privacy rights [17].

This presents a fresh obstacle for the networks that support the IoT in the form of the data island dilemma. In actual use, however, both machine learning (ML) and big data tools is capable to effectively learn and analyze a large quantity of data. In real-world applications of edge computing, the data are frequently created on the UEs themselves and then spread out across multiple networks (sometimes on a massive scale). Considering this, an improved decentralized ML approach at the edge of network has been presented, and it goes by the name federated learning (FL) [4]. This method is intended to examine the dispersed data. FL typically consists of a parameter server (coordinator) and a group of users. Each user stores raw data locally and works together with the other users to accomplish the same learning goal. To be more specific, every user perform training on its own data, and then regularly updates the local model that is stored on the coordinator. Once all these local models have been aggregated, the coordinator will send the global model back out to the users and continue doing so until the global model converges. FL markedly decreases the cost of data transmission, helps ease the strain on backbone networks, and provides improved privacy and security [2]. This aids in minimizing substantial communication cost between UEs and the coordinator and prevents the possibility of a bottleneck occurring on the coordinator when as opposed to the traditional FL [12], [14]. Nevertheless, under this design, which is the same as that used in the FL platforms that came before it, UEs such as cellphones and integrated sensor nodes that only have a limited number of resources and a diverse set of those resources can also autonomously undertake model training. When it comes to training massive models on these UEs with no breaching the resource restraints—that is, they are unable to provide such a significant resource prerequisite in the FL protocol—this becomes a critical issue that needs to be addressed. In the nutshell, this research will discuss a number of issues that need to be resolved before FL can be fully implemented. These issues include data that is not independent and distributed identically across the network (also known as non-iid data), as well as elevated communication overhead caused by the transmission of data of vast quantities of local model upgrades.

A. Motivation and Novelties

Herein, we want to answer a basic question: can the efficiency of heterogeneity IoT networks be improved by using FL while still ensuring convergence, even though edge nodes have limited communication and compute assets? To do this, we consider the following intrinsic problems that could hinder FL efficiency in cellular IoT. 1) *Non-iid Data:* Since UEs in decentralized IoT networks do not all capture the same amount of data, the volume and dispersion of the evidence acquired will vary greatly. Because of this, FL techniques are unstable and have diverging convergence when using random and regular sampling approaches to pick user involvement. 2) *Heterogeneity of UEs:* The performance of synchronized FL strategies may suffer due to the wide variation in UEs' computational capabilities, bandwidth gains, and power consumption. 3) *Limited Bandwidth:* Many UEs may make up the IoT network and work together to develop a common model of knowledge. Nevertheless, in an IoT network that makes use of FL, it is not essential to compel all UEs to engage in every interaction round; rather, each unit could be engaged in many training rounds. Also, once the number of UEs surpasses a certain barrier, it might be not feasible to obtain dependable and low-latency connections for the purpose of uploading local models because of the restricted bandwidth. It is preferable in this instance for users to participate in fewer rounds than in all of them.

Doi: https://doi.org/10.54216/JISIoT.070106
Received: March 26, 2022 Accepted: October 21, 2022

The proposed solution for resource allocation in IoT using Federated Learning (FL) involves several steps. Firstly, the IoT devices that need to share their resources for a common task are identified. Secondly, a set of representative IoT devices is selected from the identified devices. These devices will act as the FL participants, which will be responsible for training a machine learning model. Thirdly, the resource allocation problem that needs to be solved is defined, such as allocating computing resources for running a machine learning algorithm. Fourthly, a machine learning model is designed that can solve the resource allocation problem using FL. This model is then trained using the data from the IoT devices. Finally, the data from the IoT devices is partitioned among the FL participants, with each participant training the model on its local data. The trained models are then aggregated to create a final model that can be used for resource allocation in IoT. This proposed FL solution for resource allocation in IoT enables multiple IoT devices to collaborate and contribute their computing resources to solve a common problem while ensuring data privacy and security.

What follows is a brief outline of how the rest of the article is structured. Section II consists of introductory material, including terminology. In Sections III and IV, the FL methodology and asset management system are presented, correspondingly, for cellular IoT networks. In Section V, the numerical results are presented, and in Section VI, the study is wrapped up.

2. Literature Overview

In this section, we take a look at the various FL approaches that are currently available and discuss how to optimise FL performance over cellular IoT. It is possible that federated averaging, often called FedAvg, is the most widely used FL method [8]. FedAvg is an algorithm for synchronously decentralized optimization. Prior to actually aggregating the results of the local model updates at a centralised server, FedAvg performs many updates of stochastic gradient descent (SGD) concurrently on UEs. In contrast to SGD, FedAvg conducts a greater number of local updates and a reduced number of global updates, which enhances the efficiency of communication. Through a series of experiments, it was demonstrated that FedAvg performs admirably on data that does not contain iid. On the other hand, the conceptual convergence assurance in real world conditions was not offered until only lately in [15]. In order to create a good initialization model, the research [16] presented individualised FL (Per -FedAvg). Inspired on model-agnostic metalearning (MAML), this model be able to be instantly adapted to the user's personal dataset. In [17], a study was conducted on SGD-based FL for hetnets. In this study, an adaptable control scheme was suggested in order to obtain the required balance between local upgrades and global aggregation stages. The research presented in [18] suggested a communication efficient FedAvg that would utilise a decentralized version of Adam optimization and encoding in order to cut down on the number of transmission cycles and the amount of data that would need to be uploaded. An asynchronous federated optimization technique was suggested by in [19], and it has been demonstrated to exhibit near-linear convergence to an optimal solution. FedProx, a generalisation of FedAvg, was first proposed in [20]. Many researchers, however, have recently shifted their focus to the dynamic provisioning of FL in the periphery of wireless networks.. three distinct scheduling approaches were suggested in [21] as a means of hastening the convergence of FL algorithms while simultaneously taking into consideration the consequences of user planning and interruption. In [22], the optimal compromise between the amount of energy used by all UEs and the amount of time needed for FL training is investigated. Each UE in this case must synchronise the dissemination of its local updates with the others. The work reported in [23] aimed to find ways to mitigate the worldwide FL loss function expansion caused by wireless networks. The compute delay of the local FL training model, on the other hand, was ignored. In [24], we saw a method for scheduling and assigning bandwidth that minimises energy consumption. It is possible that using this method will reduce UEs' overall energy consumption.

3. Methodology

Many IoT devices will be linked to IoT networks to collect data for a variety of purposes, including public safety, weather monitoring, energy management, transportation, and others. In terms of electricity and processing power, for example, UEs in IoT networks may differ greatly. At round g, we change the local objective of k UE as follows to address two major challenges in conventional federated optimization [5].

Doi: https://doi.org/10.54216/JISIoT.070106
Received: March 26, 2022 Accepted: October 21, 2022

$$f_i'(\mathrm{w}) \triangleq f_i(\mathrm{w}) + \frac{\mu p_k}{2}\|\mathrm{w}-\mathrm{w}_g\|^2 \forall i \in \mathcal{D}_k \qquad (1)$$

Then, we adjust the client's parameters in eq(1), as follows:

$$\mathrm{w}_{g,\ell+1}^k = \mathrm{w}_{g,\ell}^k - \lambda_{g,\ell}\nabla F_k'\left(\mathrm{w}_{g,\ell}^k, \xi_{g,\ell}^k\right) \qquad (2)$$

Herein, we investigate the convergence of the our scheme and offer a high bound of $\mathbb{E}\{F(\mathrm{w}_G)\} - F(\mathrm{w}^*)$, in which w_* indicates the optimum comprehensive model equivalent to the least of the global cost F. To simplify the analysis, we first accept some hypotheses about the altered local objective, which are used extensively in [10-15].

$$F_k'(\mathrm{w}) \le F_k'(\tilde{\mathrm{w}}) + \langle \nabla F_k'(\tilde{\mathrm{w}}), \mathrm{w} - \tilde{\mathrm{w}}\rangle + \frac{\Gamma}{2}\|\mathrm{w}-\tilde{\mathrm{w}}\|^2 \forall k. \qquad (3)$$

When $F_k(\cdot)$ is curved, $F_k'(\cdot)$ turn out to be μ_k-greatly curved :

$$F_k'(\mathrm{w}) \ge F_k'(\tilde{\mathrm{w}}) + \left\langle \nabla F_k'(\tilde{\mathrm{w}}), \mathrm{w} - \tilde{\mathrm{w}}\right\rangle + \frac{\mu_k}{2}\left\|\mathrm{w}-\tilde{\mathrm{w}}\right\|^2 \forall k. \qquad (4)$$

It could be noticed that $\sum_{k\in\mathcal{K}_{tot}} \mu_k = \mu \sum_{k\in\mathcal{K}_{tot}} p_k = \mu$.

$$\mathbb{E}\left\{\left\|\nabla F_k'\left(\mathrm{w}_{g,\ell}^k, \xi_{g,\ell}^k\right)\right\|^2\right\} \le \delta. \qquad (5)$$

To make things simpler, we presume that $\lambda_g = \ell \forall \ell$, such that every round run with the same learning rate, and thereby the global updates compute as follow:

$$\overline{\mathrm{w}}_{g,\ell+1} \triangleq \sum_{k\in\mathcal{K}_{tot}} p_k\left(\mathrm{w}_{g,\ell}^k - \lambda_g \nabla F_k'\left(\mathrm{w}_{g,\ell}^k, \xi_{g,\ell}^k\right)\right) \qquad (6)$$

Under complete user involvement in eq(4), we always have $\overline{\mathrm{w}}_{g,\ell+1} = \sum_{k\in\mathcal{K}_{tot}} p_k \mathrm{w}_{g,\ell+1}^k$, however it does not hold for the suggested FL owing to the uncertainty of selection approach.

$$\mathbb{E}\{\frac{1}{K_g}\sum_{k\in\mathcal{K}_g} \mathrm{w}_{g+1}^k\} = \overline{\mathrm{w}}_{g+1}. \qquad (7)$$

For $\mathrm{w}_{g+1} \triangleq (\frac{1}{K_g})\sum_{k\in\mathcal{K}_g} \mathrm{w}_{g+1}^k$, the anticipated *divergence* between w_{g+1} and $\overline{\mathrm{w}}_{g+1}$ is described by the subsequent formulation. Given that $\{\lambda_g\}_{\forall g}$ is a nonincreasing order with a decay as $\lambda_g \le \left[\frac{\lambda_0}{1+ag}\right]$ for every no-negative factor > 0 , the anticipated upper limit of $\|\mathrm{w}_{g+1} - \overline{\mathrm{w}}_{g+1}\|^2$ could be formulated as:

$$\mathbb{E}\left\{\left\|\mathrm{w}_{g+1} - \overline{\mathrm{w}}_{g+1}\right\|^2 \middle| k \in \mathcal{K}_g\right\} \le \frac{L^2\lambda_0^2\delta}{K_g(1+ag)^2}. \qquad (8)$$

By regarding the previous Expectations, the global update w∗ , the learning rate $\lambda_g \le \left[\frac{\lambda_0}{1+ag}\right]$ with $\lambda_0 \le \left[\frac{2}{\mu+\Gamma}\right]$ and $\varepsilon_0 = \|\mathrm{w}_0 - \mathrm{w}^*\|^2$, the anticipated convergence upper limit for G rounds could be formulated as:

$$\mathbb{E}\{F(\mathrm{w}_G)\} - F(\mathrm{w}^*) \le \frac{\Gamma}{2}\left(\frac{L^2\lambda_0^2\delta}{K_G(1+aG)^2} + \prod_{i=0}^{G-1}\left(1 - \frac{2\lambda_0\mu\Gamma}{(\mu+\Gamma)(1+ia)}\right)\varepsilon_0\right). \qquad (9)$$

On the other hand, by fixing the learning rate $\lambda_g = \left[\frac{2}{\mu+\Gamma}\right] \forall g$, the anticipated convergence upper limit for G rounds could be formulated as:

$$\mathbb{E}\{F(\mathrm{w}_G)\} - F(\mathrm{w}^*) \le \frac{\Gamma}{2}\left(\frac{4L^2\delta}{K_G(\mu+\Gamma)^2} + \left(1 - \frac{4\mu\Gamma}{(\mu+\Gamma)^2}\right)^G\varepsilon_0\right). \qquad (10)$$

Doi: https://doi.org/10.54216/JISIoT.070106
Received: March 26, 2022 Accepted: October 21, 2022

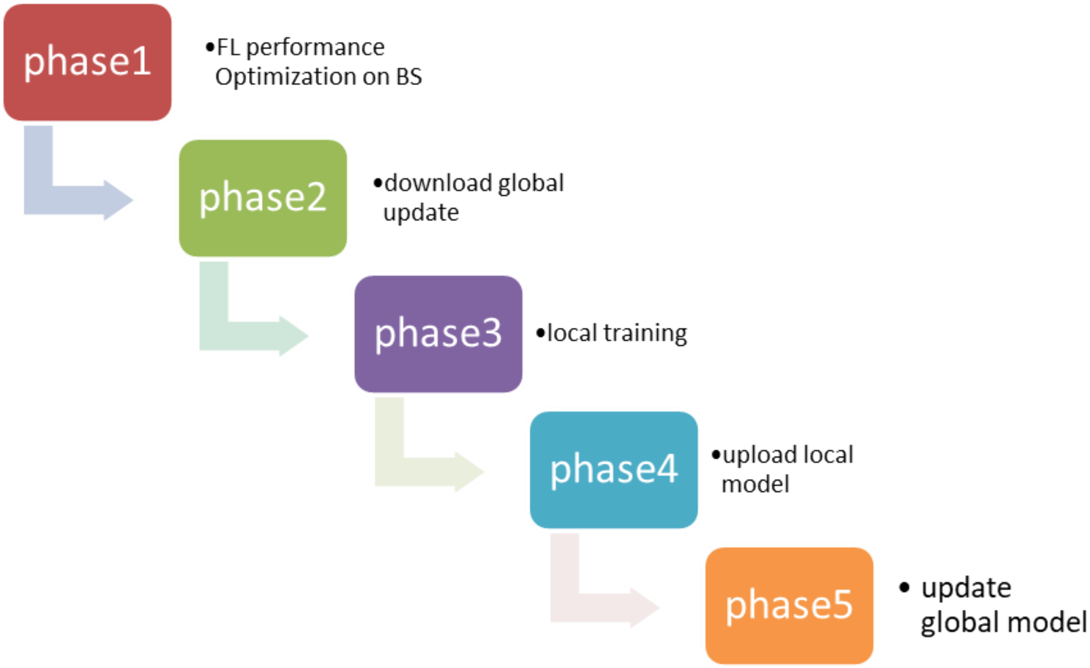


Figure 1: illustration of the main phases of proposed FL scheme

Putting it into practice: we talk about how to choose other factors besides the learning rate to effectively execute the proposed strategy. First, UEs choose an appropriate value for L, the number of local updates required to produce an approximation of the solution that satisfies some threshold of local accuracy (see Figure 1). Since w^{k}_{g+1} will converge only to an ideal solution of the local cost function if L is sufficiently large, the proposed method becomes the one-short averaging [12]. Contrarily, the proposed approach with a tiny L will place a significant strain on international communications. Therefore, not only is it important to ensure the convergence of the proposed approach but also to minimize communication overhead, but this requires setting L to an adequate number. To choose K_g, the convergence rate depends on it less than on G and L. Therefore, it is possible to tailor the number of users participating in the training to be minimal while yet ensuring excellent quality of training parameters communicated over communication channels and a convergence rate that is appropriate for IoT networks with many UEs.

Having gained this understanding in Section III, we can now design an allocation mechanism to maximise FL functionality in wireless IoT environments. Hereafter, we will refer to the steps taken to implement the suggested FL scheme until convergence as "one FL process." Fig. 2 depicts the five-step process that makes up the proposed method to aid FL. Compared to the previous FL, an extra phase is included to boost the performance of FL (e.g., in terms of power usage and training duration). Before each communication round, the BS performs this action to prepare to execute the suggested FL scheme. In fact, the BS is often provided with substantially larger compute power than UEs for executing tasks. Similarly, recent efforts on the FL for wireless communications have embraced this premise.

A. Proposed Route-Navigate Scheme

It is worth noting the functions $E_{co,k}$, $t^{dl}_{co,k}$, $t^{ul}_{co,k}$, SNR^{dl}_{k} , and $\mathrm{SNR}^{ul}_{k} \forall \mathrm{K}$ are neither curved nor bowl-shaped in $(\boldsymbol{\rho},\mathbf{b})$, which could be validated by examining the Hessian matrix. Consequently, the related

Doi: https://doi.org/10.54216/JISIoT.070106
Received: March 26, 2022 Accepted: October 21, 2022

objective as well as condition are nonconvex. The next section presents an efficient route-Navigate approach for solving issue:

$$\min_{\boldsymbol{\rho},\mathbf{f},\mathbf{b},\boldsymbol{\vartheta},\mathbf{t}} \eta E_g(\boldsymbol{\rho}^{ul},\mathbf{f},\boldsymbol{\vartheta}^{ul}) + (1-\eta)T_g^X(\mathbf{t}) \text{ s.t. } r_k^x \geq \vartheta_k^x \forall k \in \mathcal{K}_g, x \in \{dl, ul\} \tag{11}$$

Wherever,

$$\begin{aligned}
E_g(\boldsymbol{\rho}^{ul},\mathbf{f},\boldsymbol{\vartheta}^{ul}) &= \sum_{k\in\mathcal{K}_g} E_k\left(\rho_k^{ul},\mathsf{f}_k,\vartheta_k^{ul}\right)\\
E_k(\rho_k^{ul},\mathsf{f}_k,\vartheta_k^{ul}) &= S\frac{(\rho_k^{ul})^2}{\vartheta_k^{ul}} + L\frac{\theta_k}{2}c_k D_k \mathsf{f}_k^2\\
T_k(\mathsf{f}_k,\vartheta_k^{ul},\vartheta_k^{dl}) &= \frac{S}{\vartheta_k^{dl}} + L\frac{c_k D_k}{\mathsf{f}_k} + \frac{S}{\vartheta_k^{ul}}\\
T_g^X(\mathbf{t}) &= \begin{cases} t_{co}^{dl} + t_{cp} + t_{co}^{ul}, & \text{if } X \text{ is Syn}\\ t, & \text{if } X \text{ is Asyn}\end{cases}
\end{aligned} \tag{12}$$

The $t \triangleq \{t_{cp}, t_{co}^{ul}, t_{co}^{dl}, t\}$, and $\boldsymbol{\vartheta} \triangleq \{\boldsymbol{\vartheta}^{ul}, \boldsymbol{\vartheta}^{dl}\}$ with $\boldsymbol{\vartheta}^{ul} \triangleq \{\vartheta_k^{ul}\}_{k\in\mathcal{K}_g}$, and $\boldsymbol{\vartheta}^{ul} \triangleq \{\vartheta_k^{ul}\}_{k\in\mathcal{K}_g}$, and $\boldsymbol{\vartheta}^{dl} \triangleq \{\vartheta_k^{dl}\}_{k\in\mathcal{K}_g}$ are recently created variables to disentangle the cost function. All restraints and the goal itself are seen to be concave and smooth. Because UEs have limited computing power and data storage, this could require more than one transmission block to finish a single global round.

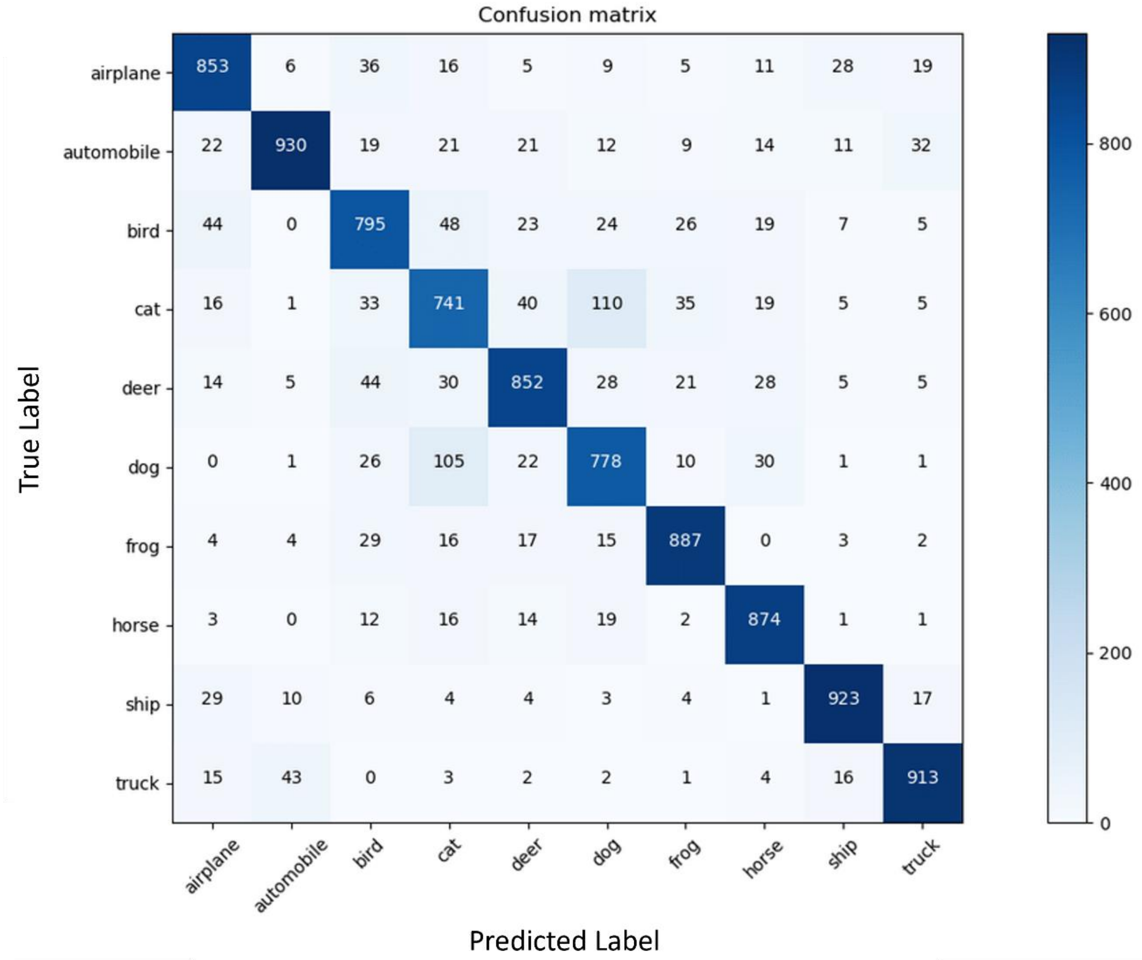
$$\begin{aligned}
\Rightarrow \quad & \{b_k^x B \log(1+\gamma_k^x) \geq \vartheta_k^x |\\
& \times \text{Prob}\left(\frac{\varphi_k \|\rho_k^x \overline{\mathbf{h}}_k\|^2}{b_k^x B N_0} < \gamma_k^x\right) \leq \epsilon\}\\
& \forall k \in \mathcal{K}_g, x \in \{dl, ul\}
\end{aligned} \tag{13}$$

which guarantees a satisfactory boundary. At this point, γ_k^x denote a new factor indicating the smooth SNR of $k-th$ UE, and ϵ denote small positive factor (close to 0) to guarantee high dependability.

4. Empirical Results

A. Data Description

Doi: https://doi.org/10.54216/JISIoT.070106
Received: March 26, 2022 Accepted: October 21, 2022



	airplane	automobile	bird	cat	deer	dog	frog	horse	ship	truck
airplane	853	6	36	16	5	9	5	11	28	19
automobile	22	930	19	21	21	12	9	14	11	32
bird	44	0	795	48	23	24	26	19	7	5
cat	16	1	33	741	40	110	35	19	5	5
deer	14	5	44	30	852	28	21	28	5	5
dog	0	1	26	105	22	778	10	30	1	1
frog	4	4	29	16	17	15	887	0	3	2
horse	3	0	12	16	14	19	2	874	1	1
ship	29	10	6	4	4	3	4	1	923	17
truck	15	43	0	3	2	2	1	4	16	913

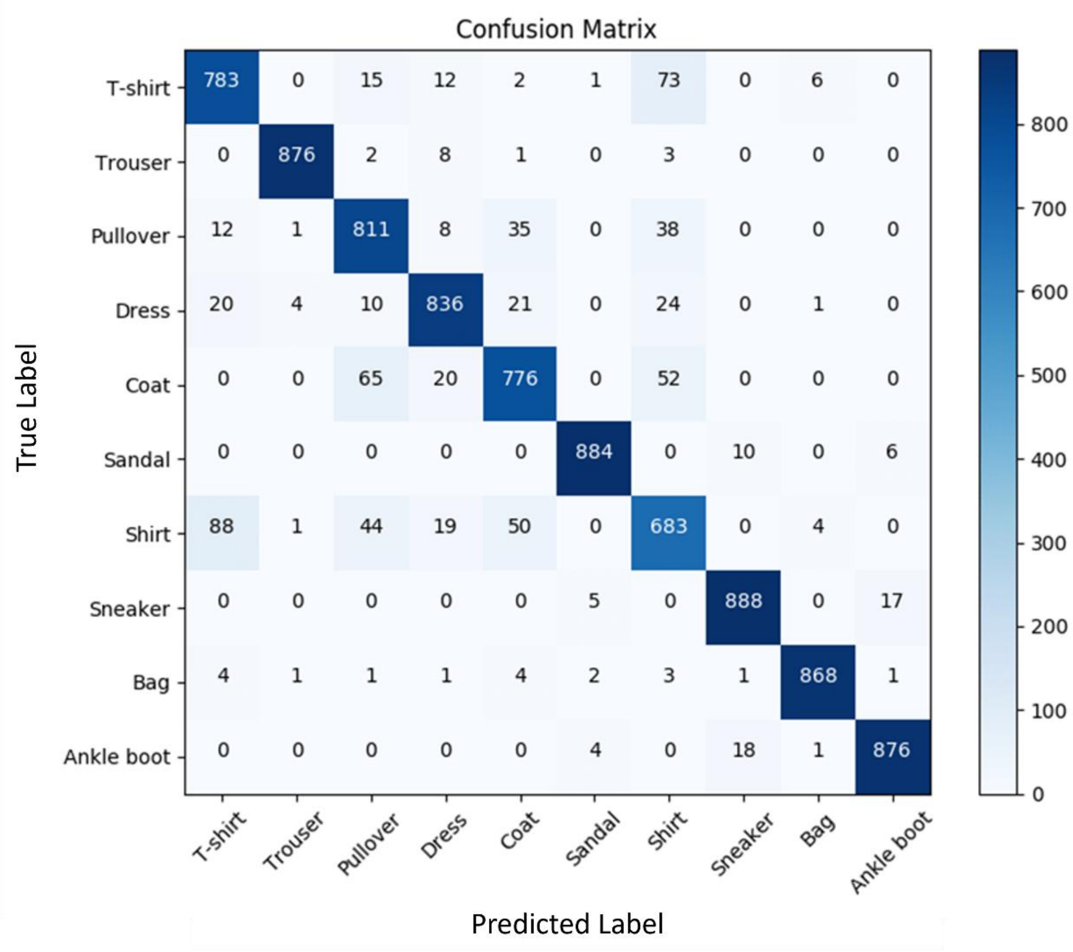
Figure 2: confusion matrix of the proposed FL scheme on the CIFAR-10 dataset.

To evaluate the efficacy of the proposed FL method in a diverse environment, we train it on 100 UEs using both Fashion-MNIST and CIFAR-10 datasets. The number of samples across UEs follows a power law, in wich every UE only has access to two classes of data. Artificial datasets are created for each of the above datasets by following the mechanism given [3].

B. Simulation Setup

For guaranteeing the convergence of the proposed FL scheme, the experiments set the $\lambda_g = \left[\frac{\lambda_0}{1+0.01g}\right]$ as fixed learning rate, in which the initial value λ_0 is thoroughly selected from the following group of values $\{0.1, 0.03, 0.01\}$. Moreover, Her initialization is used to define initial parameters $\boldsymbol{w}_0 = 0$. For both datasets, the batch size is set to of 64 and 16 for both realistic and artificial samples, correspondingly. To validate the effectiveness of the proposed FL scheme, fair comparisons is performed against FedAvg, Per-FedAvg, FL. In these comparisons, the number of chosen UEs per round is set fixed for all deemed FL approaches. For each UE, the local data is divided into 80% for training and 20% for evaluation. The implementation of FL solutions is done with TensorFlow, running on python 3.9 environment.

Doi: https://doi.org/10.54216/JISIoT.070106
Received: March 26, 2022 Accepted: October 21, 2022



True Label \ Predicted Label	T-shirt	Trouser	Pullover	Dress	Coat	Sandal	Shirt	Sneaker	Bag	Ankle boot
T-shirt	783	0	15	12	2	1	73	0	6	0
Trouser	0	876	2	8	1	0	3	0	0	0
Pullover	12	1	811	8	35	0	38	0	0	0
Dress	20	4	10	836	21	0	24	0	1	0
Coat	0	0	65	20	776	0	52	0	0	0
Sandal	0	0	0	0	0	884	0	10	0	6
Shirt	88	1	44	19	50	0	683	0	4	0
Sneaker	0	0	0	0	0	5	0	888	0	17
Bag	4	1	1	1	4	2	3	1	868	1
Ankle boot	0	0	0	0	0	4	0	18	1	876

Figure 3: confusion matrix of the proposed FL scheme on the Fashion-MNIST dataset.

C. Numerical Results

To evaluate how well a set of categorization models performs on test data, statisticians use a matrix called the confusion matrix. Only if the actual values of the test data are provided, it can be computed. The matrix itself can be simply comprehended, but the accompanying terminologies may be difficult. It is also called an error matrix since it displays the model's execution defects in a matrix form. Thus, detailed performance of the proposed framework on fashion-MNIST is given in Figure 2. As noted, the proposed FL scheme can effectively recognize the data class with almost zero confusion. Similarly, a detailed performance of the proposed framework on CIFAR-10 is given in Figure 3. As noted, the proposed FL scheme can effectively recognize the data class with low confusion.

Doi: https://doi.org/10.54216/JISIoT.070106
Received: March 26, 2022 Accepted: October 21, 2022

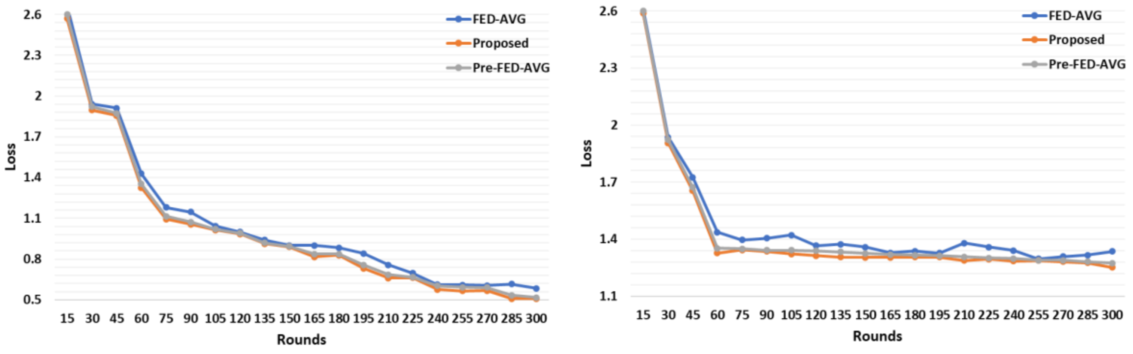


Figure 4: performance vs versus the number of communication rounds lobal rounds on actual (left) and artificial (right) data from Fashion-MNIST.

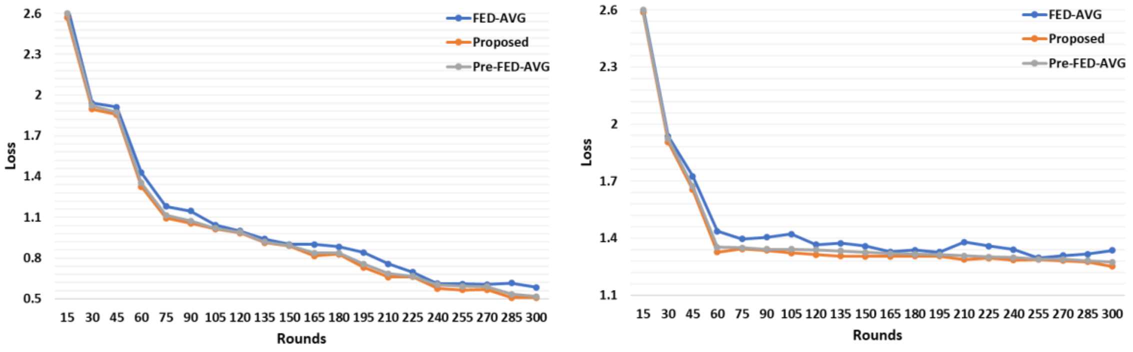


Figure 5: performance vs versus the number of communication rounds lobal rounds on actual (left) and artificial (right) data from CIFAR-10.

Figure. 4 indicates the convergence of the proposed FL scheme for both actual and artificial data from fashion-mnist. The learning rate of the competing methods is decayed in the same way as with the proposed FL scheme. The findings prove that the proposed FL scheme can significantly surpasses the competing methods on both actual and artificial data sets. The proposed system is shown to be more stable and to converge faster than competing methods, in addition to having high results. Further evidence that the weighted proximate term is an efficient tool for mitigating the unfavorable consequences of the random sampling method for selecting user involvement in a multi-faceted environment.

Junction of our solution is shown for both real and simulated CIFAR-10 data in Figure. 5. The proposed FL scheme's decline of the learning rate is like that of the competing approaches. Results show the suggested FL approach can greatly outperforms the alternatives on real and synthetic data sets. It is demonstrated that the proposed system is superior to alternative approaches, both in terms of stability and convergence speed. More proof that the weighted proximate term is a useful instrument for reducing the drawbacks of the random sampling technique when choosing user participation in a complex setting.

Doi: https://doi.org/10.54216/JISIoT.070106
Received: March 26, 2022 Accepted: October 21, 2022

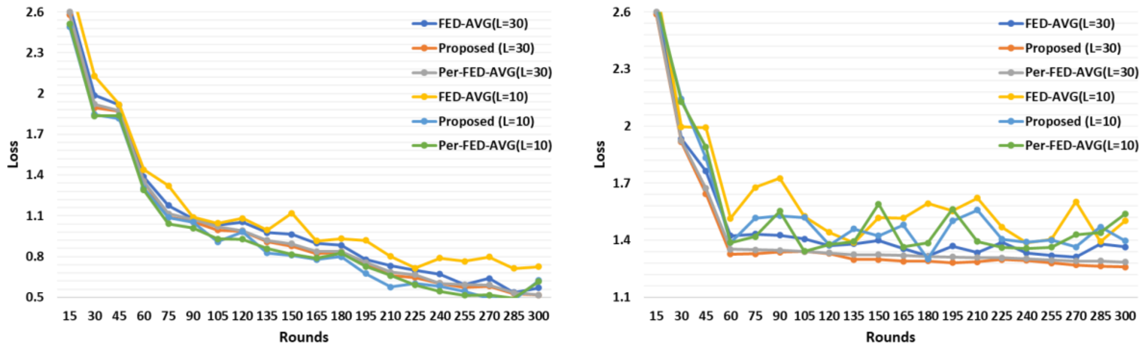


Figure 6: performance vs versus the number of communication rounds lobal rounds on actual (left) and artificial (right) data from Fashion-MNIST under different local iterations.

We examine the impact of $L = 10 \ and \ L = 30$ local iterations on the efficiency of the proposed FL algorithm in Figure. 6. The results show that in every configuration, the proposed scheme performs better than competing methods. A bigger L also expedites convergence and improves resilience against the instabilities shared by all FL algorithms when used to non-iid data. One-short averaging can occur in FL scheme if L is quite large. Allowing a suitable value of L is helpful since it increases the convergence speed and avoids divergence of the suggested FL scheme.

5. Conclusion

To address the disparity between UE data and UE features in federated systems, we present an effective FL method that uses a weighted proximal term, an adaptation of FedAvg. As a result of its unbiased sampling technique, the suggested FL algorithm only requires a tiny fraction of UEs to engage in training in each round. We have analyzed the performance of the suggested FL method under the premise of substantially convex and seamless FL's issue. Our findings were validated by experimental evidence on both actual and artificial data sets, showing that the suggested FL algorithm stabilizes and is more robust than FedAvg in highly diverse settings. Using the suggested FL approach, we then define a wireless IoT resource allocation problem with the goal of minimizing either total energy usage or timeframe.

References

[1]. Sharma, S. K., & Wang, X. (2017). Live data analytics with collaborative edge and cloud processing in wireless IoT networks. IEEE Access, 5, 4621-4635.
[2]. Preuveneers, D., Rimmer, V., Tsingenopoulos, I., Spooren, J., Joosen, W., & Ilie-Zudor, E. (2018). Chained anomaly detection models for federated learning: An intrusion detection case study. Applied Sciences, 8(12), 2663.
[3]. Sisinni, E., Saifullah, A., Han, S., Jennehag, U., & Gidlund, M. (2018). Industrial internet of things: Challenges, opportunities, and directions. IEEE transactions on industrial informatics, 14(11), 4724-4734.
[4]. Ferreira, P. V. R., Paffenroth, R., Wyglinski, A. M., Hackett, T. M., Bilén, S. G., Reinhart, R. C., & Mortensen, D. J. (2018). Multiobjective reinforcement learning for cognitive satellite communications using deep neural network ensembles. IEEE Journal on Selected Areas in Communications, 36(5), 1030-1041.
[5]. Jeong, E., Oh, S., Kim, H., Park, J., Bennis, M., & Kim, S. L. (2018). Communication-efficient on-device machine learning: Federated distillation and augmentation under non-iid private data. arXiv preprint arXiv:1811.11479.
[6]. Smith, V., Chiang, C. K., Sanjabi, M., & Talwalkar, A. S. (2017). Federated multi-task learning. Advances in neural information processing systems, 30.
[7]. Mao, Y., You, C., Zhang, J., Huang, K., & Letaief, K. B. (2017). A survey on mobile edge computing: The communication perspective. IEEE communications surveys & tutorials, 19(4), 2322-2358.

Doi: https://doi.org/10.54216/JISIoT.070106
Received: March 26, 2022 Accepted: October 21, 2022

[8]. Huang, L., Yin, Y., Fu, Z., Zhang, S., Deng, H., & Liu, D. (2018). LoAdaBoost: Loss-based AdaBoost federated machine learning with reduced computational complexity on IID and non-IID intensive care data. arXiv preprint arXiv:1811.12629.

[9]. H. S. Lee and D. E. Lee, "Resource allocation in wireless networks with federated learning: Network adaptability and learning acceleration," *ICT Express*, 2022, doi: 10.1016/j.icte.2022.01.019.

[10]. Xu, Z., Wang, Y., Tang, J., Wang, J., & Gursoy, M. C. (2017, May). A deep reinforcement learning based framework for power-efficient resource allocation in cloud RANs. In 2017 IEEE International Conference on Communications (ICC) (pp. 1-6). IEEE.

[11]. Liaqat, M., Chang, V., Gani, A., Ab Hamid, S. H., Toseef, M., Shoaib, U., & Ali, R. L. (2017). Federated cloud resource management: Review and discussion. Journal of Network and Computer Applications, 77, 87-105.

[12]. Liaqat, M., Chang, V., Gani, A., Ab Hamid, S. H., Toseef, M., Shoaib, U., & Ali, R. L. (2017). Federated cloud resource management: Review and discussion. Journal of Network and Computer Applications, 77, 87-105.

[13]. Bittencourt, L., Immich, R., Sakellariou, R., Fonseca, N., Madeira, E., Curado, M., ... & Rana, O. (2018). The internet of things, fog and cloud continuum: Integration and challenges. Internet of Things, 3, 134-155.

[14]. Hameed, A., Khoshkbarforoushha, A., Ranjan, R., Jayaraman, P. P., Kolodziej, J., Balaji, P., ... & Zomaya, A. (2016). A survey and taxonomy on energy efficient resource allocation techniques for cloud computing systems. Computing, 98, 751-774.

[15]. Lee, Y. H., Huang, K. C., Shieh, M. R., & Lai, K. C. (2017). Distributed resource allocation in federated clouds. The Journal of Supercomputing, 73, 3196-3211.

[16]. Fung, S. Y. K., Raman, K. K., & Zhu, X. K. (2017). Does the PCAOB international inspection program improve audit quality for non-US-listed foreign clients?. Journal of Accounting and Economics, 64(1), 15-36.

[17]. Caldas, S., Konečny, J., McMahan, H. B., & Talwalkar, A. (2018). Expanding the reach of federated learning by reducing client resource requirements. arXiv preprint arXiv:1812.07210.

[18]. Chen, F., Luo, M., Dong, Z., Li, Z., & He, X. (2018). Federated meta-learning with fast convergence and efficient communication. arXiv preprint arXiv:1802.07876.

[19]. Yu, Z., Hu, J., Min, G., Lu, H., Zhao, Z., Wang, H., & Georgalas, N. (2018, December). Federated learning based proactive content caching in edge computing. In 2018 IEEE Global Communications Conference (GLOBECOM) (pp. 1-6). IEEE.

[20]. Samie, F., Tsoutsouras, V., Bauer, L., Xydis, S., Soudris, D., & Henkel, J. (2016, December). Computation offloading and resource allocation for low-power IoT edge devices. In 2016 IEEE 3rd world forum on internet of things (WF-IoT) (pp. 7-12). IEEE.

[21]. Chen, M. H., Liang, B., & Dong, M. (2017, May). Joint offloading and resource allocation for computation and communication in mobile cloud with computing access point. In IEEE INFOCOM 2017-IEEE Conference on Computer Communications (pp. 1-9). IEEE.

[22]. Tanaka, H., Yoshida, M., Mori, K., & Takahashi, N. (2018). Multi-access edge computing: A survey. Journal of Information Processing, 26, 87-97.

[23]. Colen, G. R., de Oliveira, L. G., Vinck, A. H., & Ribeiro, M. V. (2016). A spectral compressive resource allocation technique for PLC systems. IEEE Transactions on Communications, 65(2), 816-826.

[24]. Cong Luong, N., Niyato, D., In Kim, D., & Wang, L. C. (2018). Efficient Training Management for Mobile Crowd-Machine Learning: A Deep Reinforcement Learning Approach. arXiv e-prints, arXiv-1812.

[25]. Samarakoon, S., Bennis, M., Saad, W., & Debbah, M. (2018, December). Federated learning for ultra-reliable low-latency V2V communications. In 2018 IEEE Global Communications Conference (GLOBECOM) (pp. 1-7). IEEE.

[26]. He, Y., Liang, C., Zhang, Z., Yu, F. R., Zhao, N., Yin, H., & Zhang, Y. (2017, September). Resource allocation in software-defined and information-centric vehicular networks with mobile edge computing. In 2017 IEEE 86th Vehicular Technology Conference (VTC-Fall) (pp. 1-5). IEEE.

Doi: https://doi.org/10.54216/JISIoT.070106
Received: March 26, 2022 Accepted: October 21, 2022

[27]. Xie, J., Yu, F. R., Huang, T., Xie, R., Liu, J., Wang, C., & Liu, Y. (2018). A survey of machine learning techniques applied to software defined networking (SDN): Research issues and challenges. IEEE Communications Surveys & Tutorials, 21(1), 393-430.

Doi: https://doi.org/10.54216/JISIoT.070106
Received: March 26, 2022 Accepted: October 21, 2022