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Sine Cosine Algorithm for Reducing Communication Costs of Federated Learning

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***Abstract*—Federated learning (FL) is a setting for machine learning (ML) in which several clients (e.g., mobile devices) train a model cooperatively under the direction of a central server (e.g., cloud server), while training data is decentralized. Due to the fact that FL clients frequently have restricted transmission capacity, communication among clients and servers needs to be reduced to enhance presentation. FL clients frequently employ Wi-Fi and must interact in unstable network environment (UNE). Existing FL aggregation techniques send and receive a huge number of weights, which dramatically reduces the accuracy of UNE. In this paper, we propose a federated SCA (FedSCA) algorithm to reduce data communication by transferring score principles rather than all client models' weights and utilizing the SCA mechanism as a weights update technique to improve the clients' models. This paper revealed that using FedSCA significantly decreased the quantity of data utilized in network communication and increased the global model's accuracy by an average of 9.87% over FedAvg and 2.29% over FedPSO. Moreover, in studies conducted on an unstable network, it demonstrated a 4.3% improvement in accuracy loss existing algorithms.**

***Index Terms*—Sine Cosine Algorithm (SCA), Convolutional Neural Network (CNN), Federated Learning, Deep Learning, optimization.**

I. Introduction

Machine learning (ML) models are getting more and more complex with the increase in the size of datasets. This is why training ML models has become a time-consuming and challenging task for data scientists [1]. In order to train ML models, it is essential to optimize the model parameters so that they are dispersed among a large number of edge devices. The currently available ML techniques are designed to be used in highly controlled environments, such as data centers, in which the distribution of data between machines occurs in a balanced and IID fashion and high-throughput networks are reachable. Recently, Federated Learning (FL) [2] have been suggested as an alternate setting: a centralized server generate the training of a shared global model from a federation of participating devices (clients). The number of participating devices, known as clients, is often relatively high, and their internet connections are either poor or unreliable.

A primary motivating example for FL emerges when the training data is derived from mobile application user interactions. Sharing prediction models is made possible by FL's ability to keep all training data on a mobile device, hence eliminating the need to store training data in a cloud-based service. To update a global model, users' mobile devices are used as nodes for computation according to their local data stored locally on their devices. By moving model training to the mobile device, this expands the applicability of local predictive models.

Conventional distributed ML [3] is not the same as FL because of the FL framework's enormous number of clients, imbalanced and non-identifiable datasets on each client, and weak network connectivity. However, there are four considerations when leveraging mobile device data for ML. Firstly, collecting or keeping private information raises the probability of data breaches. Secondly, mobile device processors lack the computational capacity required for ML (i.e., low computational capability). Thirdly, as mobile devices cannot connect to wired networks, maintaining a stable network environment is difficult because Wi-Fi connections are prevalent. Finlay, There is a considerable cost associated with acquiring and placing a considerable quantity of source data on a server to be stored.[4].

In order to design a successful ML model, especially for artificial neural network (ANN) weights, it is essential to minimize the quantity of the gathered data, enhance the security of the data collected, improve the stability of an unstable network environment (UNE), and reduce the number of training parameters. As the ANN is trained, its back-propagation mechanism adjusts its weights. In order to address the aforementioned challenges, the research on FL has consistently progressed, enabling the use of large amounts of data on mobile devices [5]. The FL technique safeguards private information by blocking data flow from multiple machines to a centralized repository [6]. Furthermore, FL keeps transmission costs to a minimum by merely uploading the learned models to the server rather than uploading enormous volumes of source data.

In standard ANN models, calculation time is significantly greater than communication time, hence several strategies are employed to minimize calculation time, including the use of graphics processing unit (GPU) accelerators and the connection of multiple GPUs. Communication in FL, on the other hand, takes more time than calculating. Therefore, FL's performance could be increased by reducing the time for a network connection. FL requires Wi-Fi connections and connected chargers due to UNE issues [7]. Therefore, in order to lower FL's communication costs, it is required to increase network transmission speed and address UNE issues. FedAvg

is the most common method of incorporating FL into a model. The goal of this paper is to adapt Sine Cosine Algorithm (SCA) [8] strategy to speed up model update. Due to the stochastic mechanism used by SCA, it requires a large number of iterations, which is in line with ML's strategy of learning via many reruns [9]. The SCA is well-suited to settings that are both varied and dynamic, like FL. We have developed a unique ANN model by applying the SCA to FL.

This paper aims to reduce network communication costs. As a way to update global models by using SCA in conjunction with FL communications. We have created the federated SCA (FedSCA) model, which uses scores like accuracy and loss instead of weights. The FedSCA network cost and accuracy are also evaluated. By comparison with other models, FedSCA was shown to be 9.87% and and 2.29% more accurate on average than FedAvg and FedPSO, respectively. Beside, We used an UNE to evaluate FedSCA. The proposed FedSCA has showed a 4.3% decrease in accuracy loss when compared to current algorithms in testing results.

The remaining structure of the paper is as follows: Section II examines past research utilizing SCA and FL. The third section discusses how the proposed method transmits the learnt model from the client to the server. The assessment of our proposed method is offered in Section IV, followed by the paper's conclusion in Section V.

II. LITERATURE REVIEW

A. Federated Learning (FL)

Formally, the objective of a Federated Learning (FL) algorithm is to solve a distributed (federated) supervised learning optimization problem [10]. A collection of $K = 1, 2, ..., K$ clients seek to concurrently optimize the global model parameters $w \in \mathbb{R}^d$ by utilizing their local data $\{X_k, Y_k\}$ of size N_k. Clients' local losses, denoted by $l_k(w, X_k, Y_k)$, are pooled to minimize a global cost function with a finite sum:

$$min_{w \in \mathbb{R}^d} \sum_{k=1}^{K} \frac{N_k}{N} l_k(w, X_k, Y_k), \tag{1}$$

FL is a learning approach for distributed datasets suggested by Konecn [2]. It prevents data leakage when training a model from datasets dispersed across several devices [11]. FL is useful since it enhances privacy and decreases communication expenses. artificial neural network (ANN) models can learn through federated learning without data or personal information intrusions. Network traffic and storage costs rise when data is sent between several devices and then stored on a centralized server. FL greatly minimizes communication costs by transmitting just model-training-derived weights. The FL procedure is outlined in Figure 1.

1) The learning model is sent from the server to all selected clients.
2) The models obtained are trained using client data.
3) Each client delivers the server its trained model.
4) The server processes and integrates the obtained models into a single updated model.

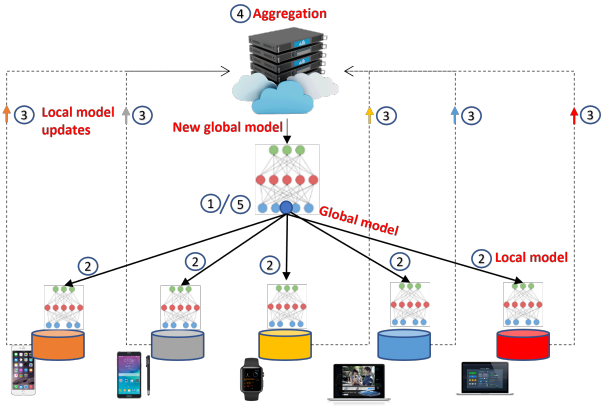

Fig. 1. The Federated Learning protocol.

5) This step is performed for each of the client's updated models from the server.

Federated Stochastic Gradient Descent (FSGD) is used in a large number of FL studies. As shown in Figure 1, the fourth step is accomplished by using FedSGD and federated averaging (FedAvg). The FedAvg is an algorithm that was developed by McMahan [2] to address some of the limitations of SGD, such as being unable to scale well with large datasets and update server-collected model data. All the clients' parameters are averaged together to produce global model parameters. When FedSGD collects weights from the server, it returns them to the client. In this method, the global model weights are changed to construct a global model once the gradient is submitted to the server to determine the mean. FedAvg leverages FedSGD and mini-batches to immediately update models on the client side while the server averages weights to produce a new global model.

In a mobile-device-aided setting, FL is intended to function Using mobile devices for network training has the drawback of forcing them to learn in an unstable network environment (UNE) [7]. Because of unreliable network conditions, a trained model may not be able to transfer its whole dataset when it is submitted to the network for evaluation.

B. Sine Cosine Algorithm (SCA)

Generally, Random solutions are usually used as a starting point for population-based optimization algorithms [12]. Objective function and search guidelines form the basis of an optimization process, which continually assesses and improves this random set, respectively. There is no guarantee that a solution will be obtained in a single run due to the fact that population-based optimization algorithms search for optimum solutions to optimization problems in a random way (i.e., stochastically) [13]. However, the possibility of finding the global optimum increases as the optimization steps (iterations) and number of random solutions increases. Although stochastic population-based optimization has many algorithmic variants, the process of optimizing is commonly separated into two stages: exploration and exploitation [14].

Optimization algorithms first combine random solutions with a high degree of unpredictability in order to obtain interesting regions in the search space. Exploitation and exploitation are two distinct phases, and random solutions are progressively altered throughout exploitation.

SCA is a new meta-heuristic approach that employs the sine and cosine functions' mathematical features. In 2015, Mirjalili developed this method [8]. This population-based optimization approach starts with a random distribution of solutions. The following equations are then applied to each individual solution.

$$C_{X_i^{itr+1}} = C_{X_i^{itr}} + C_1 \times \sin(C_2) \times \mid C_3 G_{B_i^{itr}} - C_{X_i^{itr}} \mid \quad (2)$$

$$C_{X_i^{itr+1}} = C_{X_i^{itr}} + C_1 \times \cos(C_2) \times \mid C_3 G_{B_i^{itr}} - C_{X_i^{itr}} \mid \quad (3)$$

, where $C_{X_i^{itr}}$ is a current solution at itr iteration in the i_{th} dimension, $G_{B_i^{itr}}$ is a best solution so far. The values of C_2 and C_3 are completely random. The search space region around the current solution can be determined by the coefficient C_1. There is no definitive boundary between $G_{B_i^{itr}}$ and $C_{X_i^{itr}}$ in the search space. Using this parameter, it is easier to explore and exploit the search space during the search. The coefficient C_1 is devoted to exploring the search space in half of the maximum number of possible iterations and the second half to exploiting the search space. C_1 is defined in terms of the following mathematical formula:

$$c_1 = a - itr_i \frac{a}{Max_{itr}} \quad (4)$$

The maximum number of SCA iterations Max_{itr} is used as a termination criteria, a is a constant (2 in this paper). It is possible for C_1 to point towards or outside $G_{B_i^{itr}}$, depending on the present solution's moment direction. There are two weights in C_1 one for exploring ($C_1 >1$) and one for exploiting ($C_1 < 1$). C_1 also avoids premature convergence at the end of each iteration. A smooth transition from sine to cosine functions, and vice versa, can be achieved using the coefficient C_1. Here is how SCA makes use of the previous two equations:

$$C_{X_i^{itr+1}} = \begin{cases} C_{X_i^{itr}} + C_1 \times \sin(C_2) \times \mid C_3 G_{B_i^{itr}} - C_{X_i^{itr}} \mid & r_4 < 0.5 \\ C_{X_i^{itr}} + C_1 \times \cos(C_2) \times \mid C_3 G_{B_i^{itr}} - C_{X_i^{itr}} \mid & r_4 \geq 0.5 \end{cases} \quad (5)$$

The SCA algorithm's phases are explained in depth in Algorithm 1.

Algorithm 1: Pseudocode of the SCA algorithm

Input: the SCA parameters (a, c_1, Number of dimensions, Number of solution, Number of iterations Max_{itr}).
Create the population of solutions.
while The current iteration itr_i less than the maximum number of iterations Max_{itr} **do**
  Compute the objective function for each solution.
  determine the best solution $G_{B_i^{itr}}$.
  Compute c_1 using Eq (4).
  Generate c_2, c_3, and c_4.
  for each solution $C_{X_{itr}}$ **do**
    for each decision variable i in $C_{X_{itr}}$ **do**
      update the current solution using Eq (5).
    end for
  end for
end while
Output: Return $G_{B_i^{itr}}$ which is the best solution.

C. Related Work

There is a lot of study on how to improve FL performance through better communication with clients. Numerous problems arise when the UNE of mobile devices is used, including group shifting, significant server load, frequent node crashes, and increasing latency. Furthermore, multi-layer models have been employed to enhance learning accuracy. However, as the layers become deeper, the number of weights for the nodes also increases. Because it increases the amount of data that must be sent between the server and the client, large data sets are a problem for FL.

There are two ways to reduce the uplink communication costs proposed by the researchers in [5] including: sketched updates, by learning the full model update and then compress it using a combination of quantization, random rotation, and subsampling prior to sending it to the server; and structured updates, by learning an update from a smaller set of variables in a more restricted space, e.g. low-rank or random mask. The proposed methods achieved lower communication costs by two orders of magnitude on recurrent and convolutional networks.To improve FL, the researchers proposed an asynchronous learning mechanism for clients and an aggregated temporally weighted local model on the server in [15]. These studies, on the other hand, might reduce UNE's accuracy.

The conventional FL paradigm also poses security implications. The weights of FL models are frequently transmitted to the server in a single batch. Communication of model weights through the Internet is potentially problematic since sensitive data may be retrieved via the reverse computation of model weights, according to [16]. Because of this, we focused on reducing server weight collection.

Before this, the majority of past research has concentrated on improving client communication and global optimization in FL. Data transmission in FL's UNE has never been studied in depth. More than one effort at FL has been made, but SCA has never been used to increase global model performance through improved network communication. A global model update approach built on the SCA architecture focuses on altering the data format sent among clients and servers to improve the performance of FL.

III. Federated Sine Cosine Algorithm

Adding extra model layers is a common way to improve the accuracy of artificial neural network (ANN) models. This is known as a "deep neural network." The number of weight parameters that must be learned grows as the number of layers increases. A considerable rise in network communication costs occurs when a model trained on a client is moved to a server in the global FL. Consequently, we propose the FedSCA

approach to transport a model-independent of its size while delivering the best loss or accuracy (i.e., score) to the server.

Before discussing the FedSCA, we will explain the FL algorithm used in previous research (i.e., FedAvg). Algorithm 2 shows the implementation of the FedAvgin FL. Line 4 selects the client who will participate in the round. Finally, the client's weight values are obtained in Lines 5 and 6. Weights acquired in Line 8 are averaged, and the global model weights are computed when this step has been completed. The client receives the server's global weights in Lines 10–13 and learns the data.

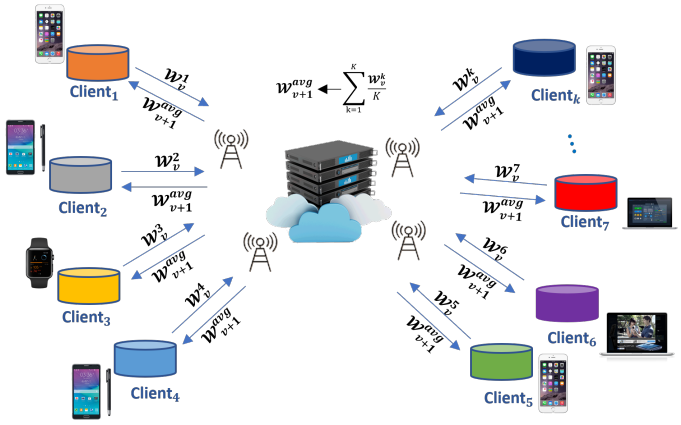

Fig. 2. Weighted aggregation processes like FedAvg receive an average of the W_t values that K clients transmit to the server and send an average of the updated $W_t + 1$ weights back to clients.

Algorithm 2: Pseudocode of the FedAvg algorithm

```
1: Function CLOUDSERVEREXECUTES :
2: initialize global model (w_0).
3: for each iteration itr = 1, 2, 3...Max_itr do
4:     S_itr= set of maximum clients.
5:     for each client k ∈ S do
6:         w^t + 1=LocalClientUpdate(k,w^t)
7:     end for
8:     w^t + 1=average the weights
9: end for
10: Function LocalClientUpdate(k,w^t) :
11: for each client epoch i=1,2,3...E do
12:     Execute the learning procedure to client k.
13: end for
14: updated w.
15: return w to server.
```

In the proposed algorithm, the FedSCA model gets the model weights from the client who provided the highest score, avoiding the need to provide model weights from all clients. Figure 3 depicts the process. Using client training's lowest loss value, the best score is achieved. 4 bytes are all that is needed for this loss value. As a result, FedSCA adjusts its weighted array using the current solution value for each member of the optimum model. Figure 3 depicts the process.

In light of the fact that the ANN weight values have been updated in Eq (5), the FedSCA weight values can be represented as follows.

$$C_{w_i^{itr+1}} = \begin{cases} C_{w_i^{itr}} + C_1 \times \sin(C_2) \times \mid C_3 G_{Bw_i^{itr}} - C_{w_i^{itr}} \mid & r_4 < 0.5 \\ C_{w_i^{itr}} + C_1 \times \cos(C_2) \times \mid C_3 G_{Bw_i^{itr}} - C_{w_i^{itr}} \mid & r_4 \geq 0.5 \end{cases} \quad (6)$$

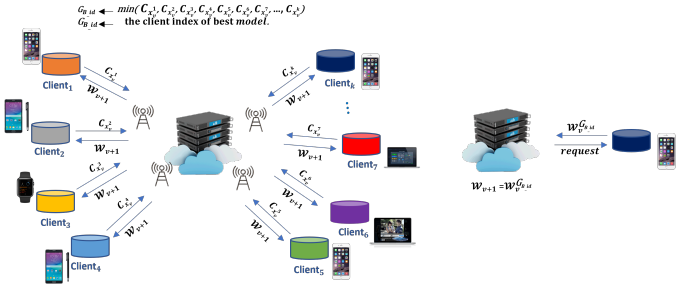

Fig. 3. The process of updating the weights of the FedSCA algorithm. The client with the best score value receives a request from the server to be used as the global model after the server receives the scores from all clients

, where $C_{w_i^{itr+1}}$ is denoted to next layer (l) wight value, $C_{w_i^{itr}}$ is the current layer (l) wight value, and $G_{Bw_i^{itr}}$ the global model layer wight value.

In Eq (6), the current ANN solution contains a weighted value assigned to each layer. Adding $C_{X_i^{itr}}$ to the prior step weight w^{t-1} yields the current step weight w^t.

Algorithm 3 presents the FedSCA conceptual algorithm according to the weight update in Eq 6. Based on Algorithm 2, the algorithm is expanded using SCA. In contrast to typical methods, the Function CLOUDSERVEREXECUTES receives just the best values and does not request w from the client on Line 6. Lines 7–8 carry out the process of identifying the client with the minimal best value among those obtained. Function A new version of the ANN's SCA implementation, LocalClientUpdate, was released. $C_{X_{itr}}$ is calculated on lines 17-19 and supplied to the server. For each epoch i, repeat the iterations (training) from Lines 20 to 23. Function The GetBestModel method (lines 25–28) asks the server for the model with the best score.

IV. Experiments

We tested FedSCA's accuracy and convergence speed, as well as conducted tests in an unstable network environment (UNE), to determine its effectiveness. Because FedAverage needed more network connections, we wanted to see whether the model's accuracy and convergence speed were enough. On the other hand, we looked at the client-server data connection costs using the CIFAR-10 dataset as an accuracy criterion for the two techniques. FedAvg and FedSCA were put to the test under different network conditions to determine their accuracy.

A. Experimental Setup

With a CPU 2.50 GHz (2 processors) with 128 gigabytes (128 gigabytes usable), Xeon(R), an Intel(R) and 465 gigabytes of memory was used for experiments. It was created using TensorFlow 2.3.0 and Keras 2.4.3.

Federated Learning's (FL) network communication performance, this research was offered in an effort to enhance it. A new data format was sent from client to server, and the distributed model's weights were altered as a result. The CNN model exhibited excellent accuracy, but it was deemed too complicated to be included in the final output. For our CNN

Algorithm 3: Pseudocode of the FedSCA algorithm

Set the SCA parameters (a, c_1, Number of dimensions, Number of solution, Number of iterations Max_{itr}).
Function CLOUDSERVEREXECUTES :
initialize global model (w_0), $G_{B_i^{itr}}$, G_{B_id}.
for each iteration $itr = 1, 2, 3...Max_{itr}$ **do**
  for each client k **do**
    G_{B_id}=LocalClientUpdate(k,G_{B_id})
    Update $G_{B_i^{itr}}$
    Update G_{B_id}
  end for
  w^{t+1}=GetBestModel(G_{B_id})
end for
Function LocalClientUpdate(k,G_{B_id}) :
initialize $C_{X_{itr}}$, a, c_1.
B= split data into batches.
Compute c_1 using Eq (4).
Generate c_2, c_3, and c_4.
for each layer l=1,2,3... **do**
  update the current solution using Eq (6).
end for
for each client epoch i=1,2,3...E **do**
  for batch b $\in$ B **do**
    update w.
  end for
end for
return $C_{X_{itr}}$.
Function GETBESTMODEL((G_{B_id}):
request to Client(G_{B_id})
receive w from Client
Return w to server.

model, we used FedAvg's example of a two-layer CNN [10]. (the first with 32 channels, the second with 64 channels, each followed by 2 x 2 maximum pooling). Table I provides a breakdown of the model's layers.

TABLE I
CNN PARAMETER SETTINGS

ID	Shape	Layer
1	5 x 5 x 32	Conv2D
2	32	Conv2D
3	5 x 5 x 64	Conv2D
4	64	Conv2D
5	1024 x 512	Dense
6	512	Dense
7	512 x 10	Dense
8	10	Dense

The experiment was carried out with the help of the CIFAR-10 data collection. For image classification, CIFAR-10 is a popular dataset. Training photographs and test images are included, as well as 32 32-pixel images from ten different categories, such as automobiles and planes. Each particle was given a random number, and the CIFAR-10 dataset was jumbled. With the exception of the dropout layer, no independent tuning method was applied to increase accuracy during training. FedSCA and FedAvg client training had a learning rate of 0.0025. Table II displays the hyperparameter value that was employed in the research.

B. Experimental Result for Accuracy

Experiment results for accuracy using the CIFAR-10 dataset are depicted in Figure 4 and Table III. For the purpose of creating this graphics, we used test accuracy as our basis.

TABLE II
PROPOSED MODEL CONSTANT

ID	Parameter	FedSCA	FedAvg
1	Batch	10	10
2	Client-epoch	5	5
3	Epoch	30	30
4	C	-	0.1, 0.2, 0.5, 1.0
5	Client	10	10

FedSCA's accuracy was better (72.41%) than FedAvg's at all 30 epochs, and it was superior from the start. C = 1.0 was FedAvg's most accurate setting, with a best accuracy of 67%. In FedAvg training, C is a constant between 0 and 1, which restricts the number of consumers used. Clients who scored at least C in each communication round were chosen from the rest of the group. As the value of C increases in Figures 4 and 5, the more accurate data is transferred between server and client, but the more data is transmitted. At C = 0.5, where data transfer costs are equivalent, the accuracy disparity widens (65.00 percent for FedSCA).

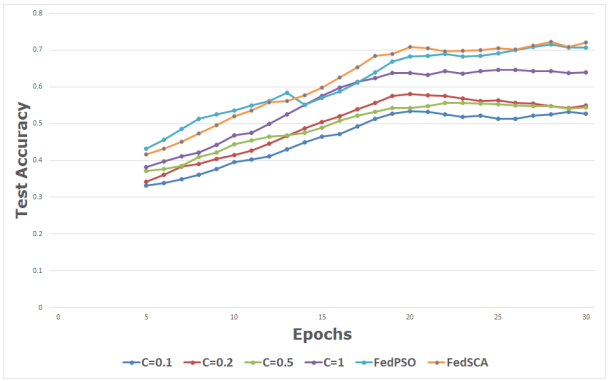

Fig. 4. A comparison of the test accuracy of different algorithms.

TABLE III
TEST ACCURACY

Algorithm	Accuracy (Testing)
FedAvg,C = 0.1	51.39%
C = 0.2	59.07%
C = 0.5	65.00%
C = 1.0	67.14%
FedPSO	70.12%
FedSCA	**72.41%**

C. Experimental Results for Unstable Network Environments

We then simulated an UNE. In each communication cycle, random data transmissions from client to server were lost. We used data discarded in ranges of 0%, 10%, 20%, and 50% to validate the accuracy discrepancy between the two methods. In order to ensure the experiment's validity, all 10 trials were done until the average value was reached. Figure IV depicts the outcome of discarding data at random for FedAvg when C

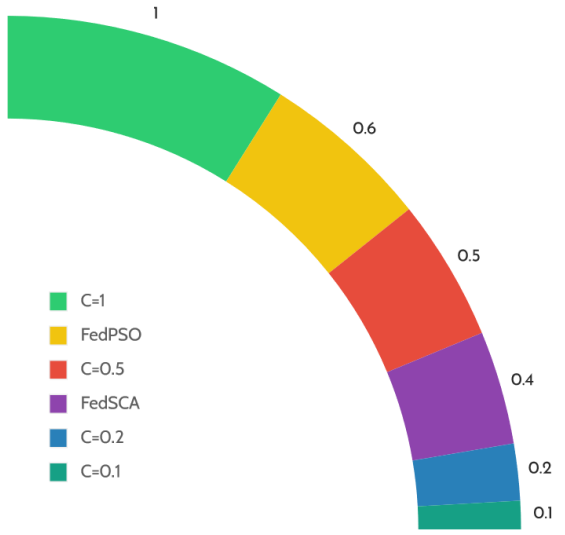

Fig. 5. A comparison of the communication cost of different algorithms.

= 1.0. FedAvg demonstrates an average accuracy reduction of 6.43 percent due to random data dropouts. Figure 8 displays the findings for FedSCA, which had a 2.43 percent decline in average accuracy. Table 5 provides accuracy findings in detail. In an experiment evaluating the model in an UNE where data cannot be delivered in its whole, FedG FedSCA's accuracy reduction was 4 percent better than FedAverage.

TABLE IV
ACCURACY AGAINST COMMUNICATION FAILURE PROBABILITY.

Algorithm	Failure Rate50%	20%	10%	0%
FedAvg,C = 1.0	59.55%	61.09%	61.48%	67.14%
FedPSO	65.47%	68.41%	69.18%	70.12%
FedSCA	**66.37%**	**68.37%**	**71.39%**	**72.41%**

V. CONCLUSION

In this paper, Sine Cosine Algorithm (SCA) is used to Federated Learning's (FL) network communication performance by utilizing the SCA mechanism to update the weights of learned models as well as reducing the amount of data being sent from clients to servers. The server-trained model's score value is distributed in the proposed method, which aggregates the results. The server receives the trained model from the highest-scoring client. Two-layer Convolutional Neural Network (CNN) is created to test the proposed algorithm on the CIFAR-10 dataset. While FedAvg had an accuracy improvement of 9.87% and and 2.29% more accurate on average than FedAvg and FedPSO, respectively. When transmission costs were equal, it improved by 4.3%.

We want to use a range of SCA implementations in the future in order to improve network connection. It is possible to avoid local minima by using dynamic multiple swarm SCA and P2P-SCA client communication. We plan to use a range of network protocols, including the gossip protocol , due to the high frequency of client drop-offs and the restricted network capacity. This is in addition to the fact that when the ANN layer rises, the model also develops in accordance. Eventually, we will conduct an experiment to see if the results can be replicated in a model with deeper layers.

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