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APPLICATION OF OPTIMAL FEDERATED RESOURCE ALLOCATION WITH 5G NETWORK IN AGRICULTURE

N.Jagadeeswari,
Assistant Professor,
Department of Computer Science and Engineering
Thanthai Periyar Government Institute of Technology,
Vellore-02.
Email id: jagadeeswarirajesh01@gmail.com

Abstract: —In most circumstances, there is a need for a bigger amount of computational power, which calls for the implementation of innovative and cutting-edge allocation strategies. It is imperative that we do not ignore the problem of coming up with efficient compression techniques that can be implemented on front haul lines. It is vitally necessary to monitor and evaluate the influence that latency has on the performance of the upper layers of the fronthaul. This is an imperative necessity. In addition, optimal resource allocation within the setting of constrained fronthaul should be the subject of further research. The loss of packets that can take place on fronthaul networks is another potentially fascinating topic that could be brought up in conversation. The fact that the fronthaul network is so diversified shouldn't come as much of a shock to anyone. It has a delay as well as a variety of connection capabilities, and because of both of these factors, the fronthaul needs to be re-configured in order to respond appropriately to the traffic load and the topology of the network. In this paper, we use Federated Learning (FL) model to optimize the resource allocation between device to Device (D2D) in 5G network. The model is designed to optimize the resources for all the users in the network , especially in the monitoring of Agricultural farms. The results of simulation shows that the proposed method has reduced delay, throughput and reduced packet loss than the other methods.

Keywords: —Cutting-Edge Allocation, Fronthaul Links, Fronthaul Network, 5G, Agricultural Engineering

I. INTRODUCTION

Communication between individual devices especially sensors installed to monitor agriculture , also known as D2D, is one of the key pillars that will be used to underpin future

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networks. This mode of communication makes it easier for traffic to unload, which in turn relieves some of the pressure that traffic causes on the system as a whole [1].

The D2D can be used for more than just dumping traffic; it can also be used to permit communication in the aftermath of catastrophic events that render the Macro BS unworkable. One example of this would be if the Macro BS was destroyed. This is frequently the case in the aftermath of natural disasters of a similar sort, such as earthquakes, floods, typhoons, and other such occurrences. The D2D concept provides a feasible answer to this problem by either determining the exact placements of the devices in question or connecting them to the operational ground network that provides the greatest amount of convenience [2].

According to the frequency range that is utilized for communication, direct-to-device (D2D) networking can be placed in either the in-band or out-band category [3]. Direct-to-device networks, often known as D2D networks, allow for device-to-device communication to take place either above or below the cellular band. D2D is carried out in the unlicensed frequency ranges known as the industrial, scientific, and medical (ISM) bands within out-of-band D2D networks. The benefits of out-of-band D2D, such as high capacity and no interference with cellular users (CUs), are counterbalanced by the difficulties in integration and maintenance that arise from the need to support several different interface types. These difficulties make the benefits of out-of-band D2D less appealing. Out-of-band D2D has many advantages, including a high capacity and the absence of interference with the CUs (such as LTE and Wi-Fi) [4].

When the CUs use D2D communications, they leave themselves open to the possibility of interference, despite the many advantages that these connections offer. This is especially the case when talking about different tactics used in-band. In the research that has been done up to this point, numerous strategies including the regulation of power and the reuse of resources have been proposed in an effort to reduce the interference. In addition, the prospective millimeter wave (mmWave) spectrum, which spans the frequency range of 30 to 300 GHz, and D2D communications [5] create an outstanding combination.

Millimeter waves, due to the delicate nature of their channel, are only capable of intermittent transmission over relatively close distances. Because of its capabilities of being precisely targeted by antenna beamforming (BF) techniques, it is a promising candidate for coexistence with D2D, which enables the development of low-mutual-interference, high-data-

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rate D2D lines. This makes it a good candidate for coexistence. As a result of this feature, it is an appealing alternative for coexisting with D2D [6].

II. RELATED WORKS

When it comes to resolving the issue of mmWave D2D NDS, the solutions that are based on ML and which are presented in this article provide a substantial improvement over the conventional methods. In this network, a mmWave device is situated in the center of a micro-BS region that spans 125 m2, and it is attempting to set up a D2D link with one of the units that is in its immediate vicinity [7].

In a typical configuration, the device in the middle would perform an exhaustive Bluetooth scan of all of the other devices in its immediate vicinity before selecting the one that could deliver the highest data rate possible via the D2D linkage. This would be done before making a decision about which device would act as the link between the devices. Before choosing a choice, this step would need to be taken. A substantial training overhead imposed by this, the throughput of the link suffers a significant reduction [8].

If the central device increases the throughput by studying one nearby device at a time and utilizing online learning to anticipate the behavior of that device, then the training overhead of the NDS process can be drastically reduced, and the throughput can be significantly increased. This can be accomplished by studying one nearby device at a time. Using the UCB and MOSS algorithms, it has been proved that the MAB-based mmWave NDS performs better than both the standard NDS and random selection [9].

The MOSS algorithm can be utilized in stochastic as well as adversarial MAB scenarios, whereas the UCB algorithm is meant to enhance the level of confidence in the action selection process with each iteration by minimizing the amount of uncertainty. Both algorithms can be used to solve the MAB problem. As a result, both potential solutions are viable options for addressing the issue that was raised by the mmWave D2D NDS. At the beginning of each cycle, a random nearby device is chosen using a random selection method to establish the D2D connection. This is done so that the connection can be established. The overhead of the NDS is cut down by a substantial amount, both the throughput and the maximum data rate are severely constrained. To create the D2D link, the UCB and MOSS algorithms have to be updated so that they can select the adjacent device that provides the highest potential maximum data rate over the long term. This allows the algorithms to choose the device that would allow for the construction of the D2D link.

III. Federated Learning

The fact that the data is dispersed over a large number of users is a challenge when it comes to the process of training a high-quality shared global model on a centralized server. Federated learning presents this challenge. Assume, for the sake of this mathematical exercise, that there are K users who are actively accessing the data at the site where they are kept.

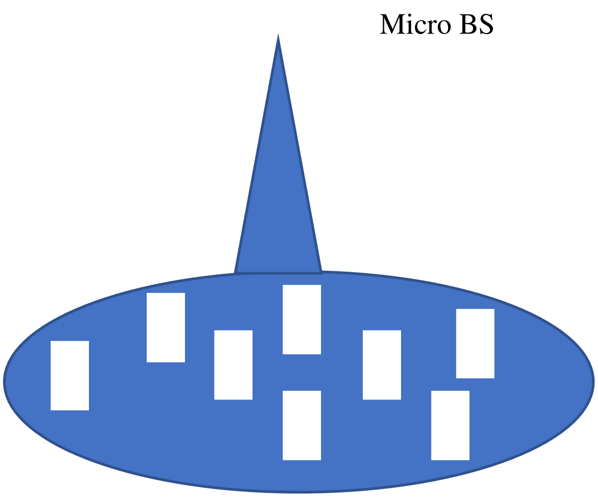

Figure 1: D2D system model

Figure 1 provides a visual representation of the simulated mmWave D2D network. The system model of D2D is shown in Figure 1.

A user could be anything from a mobile phone to a wearable device to the data warehouse of a healthcare institution; these are just some of the possibilities that are possible.) Let us characterize the data distribution that is related with user k by Dk, and let us let nk signify the number of samples that are available from user k. Finding a solution to an empirical risk reduction problem of the kind is essential if one is to be successful in overcoming the barrier posed by federated learning as in Eq.(1)

$$\min F(w) = \sum_{k=1}^{N} F_k \frac{n_k}{n} \qquad (1)$$

where

w - model learnt parameter.

$n=\sum n_k$ - sample size

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The f_i implies the loss function using input-output pair $\{x_i,y_i\}$. such that, $x_i \in R^d$ and $y_i \in R$ or $y_i \in \{-1, 1\}$.

Federated averaging is the name given to the straightforward method that can be used to the complicated issue of federated learning. It has been demonstrated that it is possible for it to function properly with data that does not follow an independent identical distribution, provided that all users employ the same model. This has been done in order to show that it is possible for it to function properly with data. However, FedAvg does not take into consideration the statistical problem given by data distributions that have a highly skewed bias in their calculations.

When training convolutional neural networks with the FedAvg algorithm, it is possible for the performance of these networks to rapidly worsen due to weight divergence. This is because of how the FedAvg algorithm works. Current research on how to overcome the statistical challenge posed by federated learning can be divided into two categories: studies that focus on finding a consensus solution and studies that focus on finding pluralistic solutions. Both categories aim to find a way to meet the challenge posed by federated learning.

Consensus Solution

When it comes to training their models, the vast majority of centralized systems make use of data that has been obtained from all of the users that are located within a particular region. By default, the centralized model is trained to minimize the loss in reference to the uniform distribution. The data distribution is calculated as in Eq.(2)

$$D = \sum_{k=1}^{K} D_k \frac{n_k}{n} \qquad (2)$$

where

D - data distribution.

As a potential solution to this problem, recent recommendations have suggested either modelling the intended distribution or pushing the data to adapt to the uniform distribution. Both of these options have been suggested as possible solutions. Both of these propositions are being taken into consideration as feasible approaches to the problem. To be successful in this endeavor, we will concentrate our efforts on a minimax optimization technique, which is also known as agnostic federated learning. This will allow us to achieve our goal (AFL). The centralized model can be optimized in this way for any goal distribution that can be

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constructed by mixing the user distributions. This technological application has only been carried out on a relatively small scale so far. The technique of giving devices that have had poor performance a greater weight in order to minimize the variance in the distribution of accuracy across a network. They offer empirical evidence to support the claim that q-FFL is more adaptable and scalable than AFL.

Making a limited quantity of material immediately accessible to all users in all regions of the world at the same time is yet another typical tactic. Both the end users and the centralized server need access to the same subset of classes, hence it is required for them to share the same subset. Sharing the same subset also makes it easier to manage. This is in addition to addressing the concern of the non-IID earlier on in the conversation.

During the time that is spent in an environment for federated learning, training data is still dispersed across a large number of users, many of whom may have unreliable and slow network connections. The equation that determines the total amount of bits that are sent in a naive federated learning setup while it is being trained is provided as in Eq.(3)

$$B \in O\left(U\left|w\right|H\Delta w + \beta\right) \tag{3}$$

where

U - total updates,

|w| - network size and

$H(\triangle w^{up/down})$ - weight entropy during the process of transmission.

β - difference between true and minimal size.

IV. Resource Allocation

When it comes to the operation of wireless network systems, the allocation of available resources is of the utmost importance. A communication system that is capable of supporting 5G will need to be both more intelligent and more adaptable in order to handle the requirements of a diverse collection of networks. This is necessary in order to accommodate the requirements. The computer system will delegate resources for tasks such as managing electricity, determining data transmission rates, positioning computers in a network, and assigning members to groups.

In the context of cellular network setups, the manner in which resources are distributed is a very essential consideration. Maintaining open communication with the customers, partners, and end users of cellular-based applications is an absolute requirement for doing so, as it is

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vitally necessary. The distribution of available resources is of significant aid in the establishment of cellular network configurations. The degree to which available resources on a network are distributed fairly has a direct consequence on how efficiently the network runs overall. There is a direct relationship between the efficiency of the network and the degree to which it is fair. This relationship is one-to-one. It is possible to distribute resources in a manner that is fair, ideal, uneven, or disproportionate. All of these outcomes are achievable. The performance of a network can range from poor to less-than-excellent all the way up to good or even flawless performance. There is no between ground.

The allocation of resources in such a way as to improve not only the efficiency of long-lasting battery-powered devices but also the quality of the service that is provided by the application is a significant obstacle that must be overcome by 5G. This is one of the significant challenges that must be met by 5G. Users have very high expectations regarding the efficient administration and distribution of available resources. The inefficient and convoluted nature of these systems is exacerbated by the antiquated services and archaic infrastructure that are characteristic of today networks. It is essential, from the perspective of the user, that the existing network resources in wireless communication networks, most notably 5G wireless networks, be allotted in an effective manner. This is the case since 5G wireless networks are the most recent generation of wireless networks. This is essential in order to guarantee the highest possible level of service (QoS).

The ever-increasing demand for 5G cellular networks offers a variety of issues, the most serious of which is the inability to efficiently manage resources. The available resources of a wireless communication network have certain specifications, and these resources have to be distributed in a manner that is consistent with the needs of the users. The spectrum resources that are accessible to the network may experience strain as a result of the exponential increase in mobile network consumption as well as the expansion of the number of devices that are linked.

V. Results and Discussions

It is possible to evaluate the effectiveness of a certain FL algorithm in a real-world setting by testing it on data that has not been seen or labeled in any way. The efficiency metric is something that is often unique to the process that is being evaluated as part of this study. The model efficacy can be determined by the proportion of instances, out of a total number of

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examples that have been determined in advance, in which the algorithm properly forecasts the result.

Measuring the error rate, also known as the percentage of wrong predictions made by the model for a certain collection of examples, is an additional way for gaining insight into the performance of the model. This rate is also known as the percentage of incorrect predictions. We make use of a test set of data that was not incorporated into the training of the FL system so that we may conduct an analysis on these performance criteria. Because of this, we are able to form a more precise judgment regarding the capabilities of the system. The selection of a performance metric may appear straightforward at first glance; however, it is not always easy to determine precisely what aspects of performance should be evaluated. The Figure 2 and Figure3 shows the average throughput and data rate.

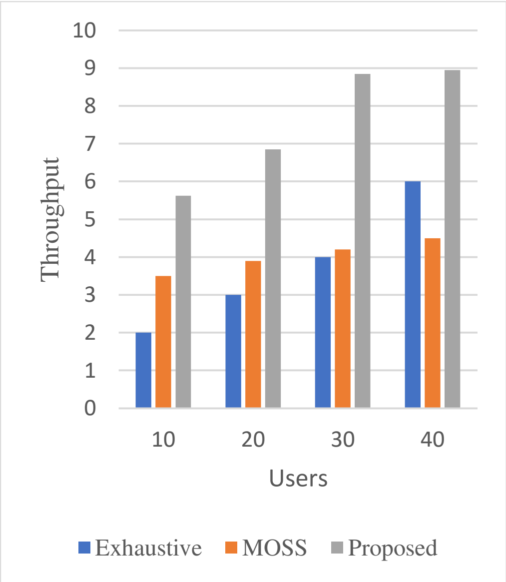

Figure 2. Average Throughput

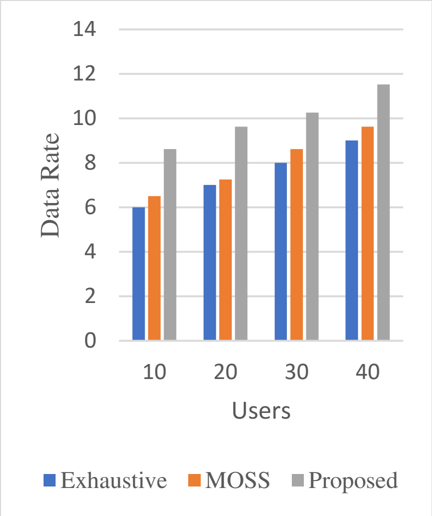

Figure 3. Average Data Rate

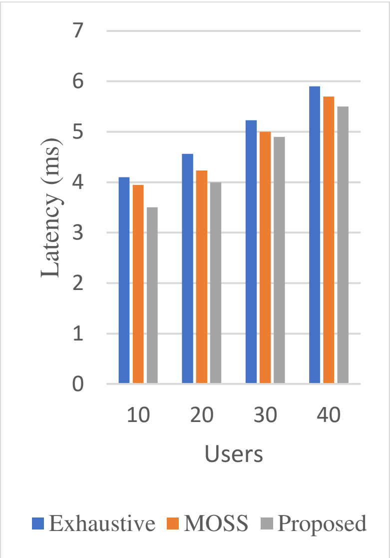

Figure 4. Latency (ms)

It is recommended that a unique performance metric be utilized whenever an unsupervised learning job such as density estimation is being carried out. Each example should be able to receive a score based on this metric, which should use a scale with continuous values. As a standard operating procedure, the release of the average log probability that the model assigns to a certain group of examples is something that is done routinely. There is a guarantee that FL algorithms will asymptotically converge to optimal behavior, and this guarantee is supported by theoretical evidence.

Moreover, there is a guarantee that FL algorithms will asymptotically converge to optimal behavior. Since optimality can only be reached through asymptotic reasoning, convergence speed is only a rough indicator of performance. One method for determining the level of

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progress that has been made is to analyze the level of development that has been made by comparing actual outcomes with estimations that are based on a baseline of what would have been achieved if the learning algorithm had not been applied. The regret meter is a tool that can be used to penalize ignorant behavior that has been acquired via experience.

VI. CONCLUSIONS

In this paper, we investigate how to improve D2D resource allocation in a 5G network by employing a federated learning (FL) model. All the individuals that make use of the network should have access to an increase in the overall usefulness of the model to the greatest extent possible. The multivariable FL optimization challenge is to gain compute offloading and cache optimization in the communication system. This will be accomplished by optimizing the multivariable FL. This is the major goal that we are trying to accomplish. By utilizing this tactic, the major concentration was directed into the stringent constraints that the application must fulfill in the real world. In addition, from the perspective of the process of locating a solution, it is recommended that self-optimization and other intelligent algorithms, such as machine learning for wireless communication applications, be implemented in CNs and developed further. This recommendation is based on the fact that it is recommended that these algorithms be developed further. These different approaches to machine learning are able to respond in an adaptable manner to the many obstacles that are present. It is possible to make real-time adjustments to the optimization parameters of the training system in order to better match the requirements of the wireless network. The findings of the simulation indicate that the method that was proposed achieves superior outcomes to those achieved by the alternatives with respect to delay, throughput, and packet loss and hence this can be installed to monitored across various agricultural farms so that it will improve better communication among various sensor nodes installed to enhance agricultural engineering.

REFERENCES

[1] Li, T., Sanjabi, M., Beirami, A., & Smith, V. (2019). Fair resource allocation in federated learning. arXiv preprint arXiv:1905.10497.

[2] Nguyen, V. D., Sharma, S. K., Vu, T. X., Chatzinotas, S., & Ottersten, B. (2020). Efficient federated learning algorithm for resource allocation in wireless IoT networks. IEEE Internet of Things Journal, 8(5), 3394-3409.

[3] Dinh, C. T., Tran, N. H., Nguyen, M. N., Hong, C. S., Bao, W., Zomaya, A. Y., & Gramoli, V. (2020). Federated learning over wireless networks: Convergence analysis and resource allocation. IEEE/ACM Transactions on Networking, 29(1), 398-409.

[4] Khan, L. U., Pandey, S. R., Tran, N. H., Saad, W., Han, Z., Nguyen, M. N., & Hong, C. S. (2020). Federated learning for edge networks: Resource optimization and incentive mechanism. IEEE Communications Magazine, 58(10), 88-93.

[5] Nguyen, H. T., Luong, N. C., Zhao, J., Yuen, C., & Niyato, D. (2020, June). Resource allocation in mobility-aware federated learning networks: A deep reinforcement learning approach. In 2020 IEEE 6th World Forum on Internet of Things (WF-IoT) (pp. 1-6). IEEE.

[6] Li, L., Fan, Y., Tse, M., & Lin, K. Y. (2020). A review of applications in federated learning. Computers & Industrial Engineering, 149, 106854.

[7] Lim, W. Y. B., Luong, N. C., Hoang, D. T., Jiao, Y., Liang, Y. C., Yang, Q., ... & Miao, C. (2020). Federated learning in mobile edge networks: A comprehensive survey. IEEE Communications Surveys & Tutorials, 22(3), 2031-2063.

[8] Shi, W., Zhou, S., Niu, Z., Jiang, M., & Geng, L. (2020). Joint device scheduling and resource allocation for latency constrained wireless federated learning. IEEE Transactions on Wireless Communications, 20(1), 453-467.

[9] Wadu, M. M., Samarakoon, S., & Bennis, M. (2020, May). Federated learning under channel uncertainty: Joint user scheduling and resource allocation. In 2020 IEEE Wireless Communications and Networking Conference (WCNC) (pp. 1-6). IEEE.