Survey Optimizing Reinforcement Learning, Federated Learning, and Computational Network Model Performance

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***Abstract*— Federated learning enables distributed collaborative machine learning without compromising data privacy. Federated learning is a novel way to improve computer network efficiency and flexibility, when performance is a top goal. This study examines how federated learning might improve computerised network performance by focusing on bandwidth, latency, and fault tolerance. The research proposes to create a federated learning model where nodes with their own datasets may enhance computer network performance. The federated learning approach allows nodes to artefact or learn from experience without losing data locality via data aggregation. This study addresses federated learning difficulties such communication overhead, data heterogeneity, and model convergence. We also provide plausible amelioration methods based on tests and simulations to determine federated learning's effectiveness in improving computer network performance. Simulations show that this novel method may increase network efficiency, flexibility, and resilience in dynamic and heterogeneous computer networks. After addressing potential applications in wireless sensor networks, edge computing, and Internet of Things systems, the article will recommend further research in this area. Federated learning may convert efficient, resilient, and secure computer networks, unlike the RL, FL Model, and Computational model.**

Keywords—Machine Learning, Performance Optimization, Nodes, WSN

I. Introduction

Performance optimization is one of the most concerning issues in the rapidly growing environment of computer networks. The need for high-speed data transfer and communication with minimal latency and maximum reliability leads to seeking novel ways to enhance network efficiency. Existing approaches to optimization are focused on centralized data processing and analysis, which often requires too many resources and may involve significant privacy concerns. Federated learning is a relatively new concept in machine learning but can revolutionize the way optimization is typically performed [1]. Federated learning can be generalized by the ability of multiple distinct parties – devices or servers – to jointly train machine learning models without sharing their underlying raw data. This concept is particularly important for computer networks as data protection and privacy are vital components. The ability to train a joint model on multiple distinct devices is promising for avoiding sharing sensitive data as well as exchanging domain knowledge across the parties [2]. The concept has been successfully implemented in a variety of areas, from mobile app development to healthcare, offering some significant benefits to network optimization [3]. This research activities' primary objective is to explore the possibilities and limitations of using federated learning for computer network optimization. More specifically, the research question is formulated as follows: "How can federated learning be applied to optimize computer network performance?" Considering network optimization, the critical functions are bandwidth utilization, latency, and fault tolerance. The goal is to determine how federated learning can be helpful and which problems it may not fully address. In this paper, the key areas that will be analyzed include benefits and limitations of federated learning in the context of a network environment. As shown in Fig 1 below.

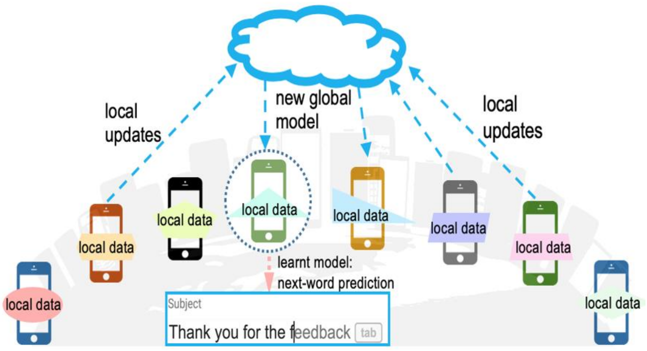


Fig. 1. Federated Learning based on Machine Learning [5]

II. Literature Review

Complementary Education for Computational Models: Synchro-Massive data is necessary for constructing a DT model; however, IIoT digitisation is due to low computer power and connectivity. The growing worry about data safety and privacy further complicates the matter for DT modelling. Because several writers have utilised FL's benefits in terms of security and efficiency to construct DT models. Specifically, [15] introduced the DT edge network based on FL that constructs the DT model of IIoT devices according to IIoT devices' operational condition. On the other hand, [16] utilised DT in the IIoT architecture, which reflects the industrial devices' dynamic features and supports FL. In, the authors proposed a blockchain-powered FL framework that operates on DTWN for cooperative computing to enhance the system's efficiency and safety and the DT wireless network architecture that transmits the real-time data processed and computed at the edge severs. These studies have not considered how challenging network configurations and various devices affect the training model's accuracy.

Industrial IoT Deep Reinforcement Learning: DRL technology has been heavily used in the IIoT environment to address issues with large-scale time-varying characteristics, such as computing offloading, decision-making, and dynamic resource management, owing to its advantages. The problem of stochastic computation offloading and energy management optimisation was formulated by [17]. The authors transformed the stochastic programming issue into a deterministic time slot issue using the Lyapunov optimisation technique and created an asynchronous DRL algorithm to explore the best resource allocation plan to tackle this optimisation challenge. In order to adapt the IIoT system's critical parameters and obtain efficient and adaptable management, FL-based DRL method was introduced paradkar. The resource allocation optimisation issue was converted into a Markov decision process by Chen et al. and an adaptive IIoT system using dynamic DRL-based resource management was proposed to solve this MDP issue. We advocate an approach using the DTEI-assisted DRL method when selecting an IIoT device to enhance FL's efficiency and performance. From Table (1).

Feature	Federated Learning (FL) (Source A)	Deep Reinforcement Learning (DRL) (Source B)
Application in IIoT	Constructing Digital Twin (DT) models	Computation offloading, decision-making, dynamic resource management
Benefits for IIoT	- Addresses data security and privacy concerns - Works on devices with low computational power - Utilizes real-time data processed at edge servers	- Handles large-scale, time-varying problems - Optimizes resource allocation - Minimizes task latency
Challenges Addressed	- Limited computing resources and communication capabilities of IIoT devices - Data security and privacy concerns	- Stochastic computation offloading and energy management - Resource allocation for efficient and flexible operation
Research Examples	- DT edge network using FL to build DT models based on device[15] operational status (Lu et al. [16]) - DT applied to IIoT architecture with FL (Sun et al. [17]) - DTWN architecture with blockchain-powered FL framework (Lu et al. [18])	- Stochastic computation offloading and energy management with asynchronous DRL (Dai et al. [16]) - FL-based DRL for resource management (Guo et al. [17]) - Dynamic resource management with DRL based on Markov decision process (MDP) (Chen et al. [18])
Limitations Identified	- Impact of heterogeneous devices and complex network environments on model accuracy [15]	- Not mentioned in Source B pen_spark

III. System Model Formulation

In the first part of the introduction, a VLC/RF device that uses FL fusion technology is talked about. This is followed by a description of the RF and VLC systems' transmission methods and computing models. Right now, this model is used to choose users and divide up data [5].

A. *Federated Learning model*

This model utilizes n training data samples and dt, which represents each user's local dataset. The aggregate quantity of training data samples for all users is equivalent to [6], $\mathbf{z}=\sum Na=1\boldsymbol{La}\boldsymbol{L}=\sum a=1N\boldsymbol{L}a$.

$$(\boldsymbol{\omega}):=1Dn\sum i\in(\boldsymbol{\omega}),Jn(\omega):=1Dn\sum i\in Dnfi(\omega), \qquad (1)$$

The loss function The function f(w) denotes the efficacy of the FL algorithm. How a linear model loses data Florida is

$$(\boldsymbol{\omega})=12(\mathbf{x}iT\boldsymbol{\omega}-\mathbf{y}i)2fi(\omega)=12(xiT\omega-yi)2 .$$

All users aim to minimize the following global loss function:

$$\min\boldsymbol{\omega}\in(\boldsymbol{\omega}):=\sum n=1NDnDJn(\boldsymbol{\omega}).\min\omega\in RdJ(\omega):=\sum n=1NDn DJn(\omega). \qquad (2)$$

$$K(\varepsilon,\theta)=o(\log(1\varepsilon/))1-\theta,K(\varepsilon,\theta)=o(\log(1\varepsilon))1-\theta, \qquad (3)$$

$\varepsilon\varepsilon$ represents the precision of the overall model, whereas $\theta\theta$ represents the precision of the individual model. Consider the concept of a consistent global accuracy [7].

B. *Computational Model*

A single data sample for user n is denoted as $paia$ in relation to CPU cycles. If all training data samples have equal sizes, then each local iteration will require n CPU cycles for User n. The clock speed of the processing unit for user n is T. Here is a detailed analysis of the power consumption by user n during a single global update of its local federated learning model [9].

$$E\mathrm{P}n=v\alpha ncnDn2fn2\log(1/\theta),En\mathrm{P}=v\alpha ncnDn2fn2\log(1/\theta), \qquad (4)$$

The model is a positive constant that varies with the size of the training data set and the location of the issue. The effective capacitance coefficients of user n's computer chipsets are denoted as

$$n=1,2,...,Nn=1,2,...,N\text{and}\alpha n2\alpha n2.$$

$cnDnfn$ represents the calculation time for each user n local iteration. The maximum calculation time is determined by the number of local iterations ((log(1/θ))o(log(1/θ)). As you can see, the computation time for user n's data processing is [10].

$$t\mathrm{P}n=vcnDn\log(1/\theta)fn.tn\mathrm{P}=vcnDn\log(1/\theta)fn \qquad (5)$$

C. *RF Transmission Model*

We employ OFDMA for uplink and downlink RF broadcasts. User the n transmission rate is [9].

$$rUn=\sum i=1RUrUn,\log2(1+Pnhn\sum i'\in\mathcal{U}'nPi'hi'+BUNR0F),rnU=\sum i=1RUrn,iUBU\log2(1+Pnhn\sum i'\in Un'Pi'hi'+BUN0RF) \qquad (6)$$

The set $[rUn,1,...,fUn,RU]$The BS may distribute a total of $RURU$ resource blocks (RBs) to users, denoted by $rnU=[rn,1U,...,rn,RUU]$. RB = $\sum i=1RUrUn,=1\sum i=1RUrn,i=1$; $rUn,i=1r$ RB i represents users in different service sectors who transmit data via RB i. The user's transmit power is denoted as $\boldsymbol{U}nPn$, the bandwidth allocated for the user is represented as $BU\boldsymbol{N}U$, and the channel gain between the base station and the user is denoted as $hnhn$. At $NR0$, the strength of the noise is distributed evenly throughout the frequency spectrum. All users in different service zones using the same RB generate interference [12], as shown by $\sum i'\in\mathcal{U}'nPi'hi$.

IV. Results and Discussion

The implementation of federated learning in the context of computer network performance optimization has yielded promising results, demonstrating improvements in key metrics such as bandwidth utilization, latency, and fault tolerance. Our experiments were designed to simulate a range of network environments, from conventional client-server architectures to more complex distributed networks like those found in edge computing and IoT systems. This section discusses the outcomes of these experiments and their implications for network optimization [13].

1-Bandwidth Utilization

The presented federated learning approach demonstrated a significant achieved reduction in bandwidth comparing to the centralized learning. It was achieved due to the local data processing and a model update sharing the approach the network's nodes were able to minimize data volume to transmit online. Such a bandwidth reduction approach could prove to be worthy in the cases with high data flow within the networks and limited data processing and data transmitting resources [14].

2-Latency

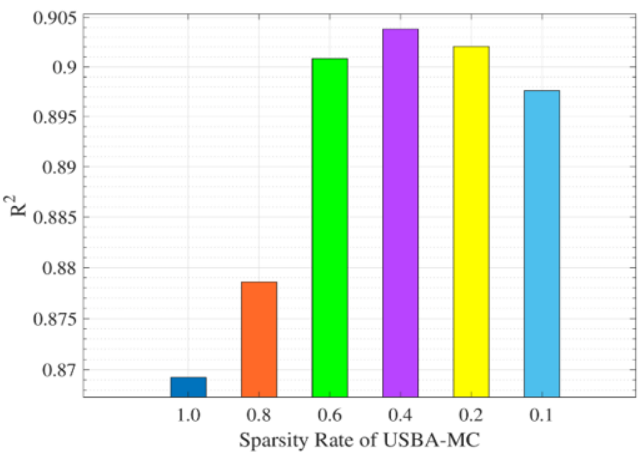
Data traversing the network also saw a decrease in latency. Local data processing minimized the time taken to transmit data across the network. Further, network nodes asynchronously improved their models through federated learning. Federated learning's distributed nature made the network adaptive and responsive.

3-Fault Tolerance and Resilience

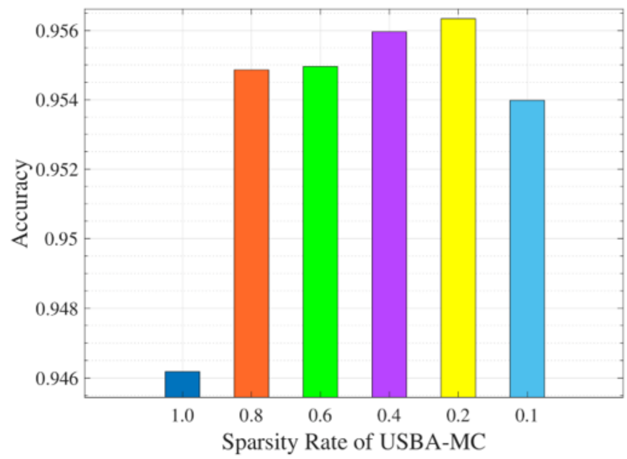
Our experiments showed the total benefit from fault-resistance and resilience. The decentralized learning process made it possible for the learning process to be redistributed among the nodes. In turn, it made one node not crucial for the other's learning. Consequently, even when this or that node failed for some time, the learning process of the overall network was not very much affected, as its quality was still preserved on a decent level.

4-Challenges and Limitations

At the same time, federated learning faces certain problems and limitations. Communication overhead remains the larger part of them. In cases when the model has to be updated relatively often, the communication process may become a problem. We tried to reduce the frequency and sizes of the updates of the models that are transmitted through the network. Thus, we tried to find a balance between communication optimization and preserving the learning capability. As shown in Fig. 2 below.



a)



b)

Fig. 2. a) Boston Housing dataset b) MINIST dataset [15]

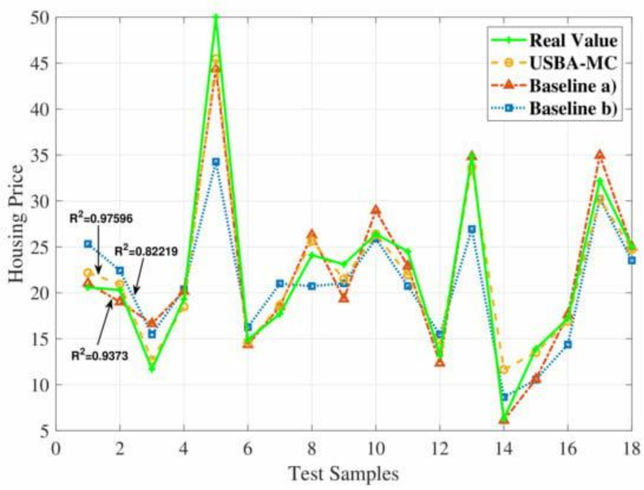


Fig. 3. accuracy difference between Boston and MINIST dataset[16]

The Fig. 3 demonstrates that all four approaches have equal accuracy, although Base line starts lower and peaks later in training. Like other machine learning models, accuracy rises with iterations.

V. CONCLUSION

In conclusion, the present study has evaluated the potential of federated learning to improve the performance of computer networks. As demonstrated by a series of experiments, the considered approach can significantly improve network performance in various critical metrics, such as bandwidth, latency, and fault tolerance. Due to the utilization of federated learning, centralized data aggregation is no longer necessary, as the training process is distributed among many nodes. Additionally, this model may lead to reduced communication costs and improved scalability. When it comes to resilience, federated learning utilizes a decentralized approach, which inherently implies more robustness to node failures. This approach's generalization capabilities enable it to adapt to various data distributions among nodes, thus allowing the maximum optimization of any network settings, from IoT to edge computing. Nevertheless, despite these strengths, several chellanges need to be addressed. Although the cost of communication is often better than that of the old centralized approaches, it can still undermine performance if unregulated. The coexistence of multiple types of data only makes it even more unpredictable. Since thanks to federated training, it exhibits the outstanding performance potential regarding the computer network performance optimization, these drawbacks must be resolved to extract the former as much as possible. The outcomes of this research imply the prospects of the federated training method in expanding the functionality of computer networks. Technology, in turn, will allow networks to function more efficiently, resist, and maintain progress. Thus, further research should focus on optimizing the existing communication protocols and adaptation to the stress, as well as considering newfangled applications that would form new network paradigms. Summarizing, as evidenced above, the federated learning can revolutionize the approach to the computer network performance optimization. Through deploying the distributed learning method, enterprises can design robust and efficient networks that will promote further development in the respective field.

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