UNIVERSITÀ DELLA CALABRIA

DIPARTIMENTO DI INGEGNERIA INFORMATICA, MODELLISTICA, ELETTRONICA E SISTEMISTICA
DIMES

Telecommunication Engineering: Smart Sensing, Computing And Networking

Improving the Quality of Federated Learning using Programmable Networks

AHMAD MAHMOD 234454

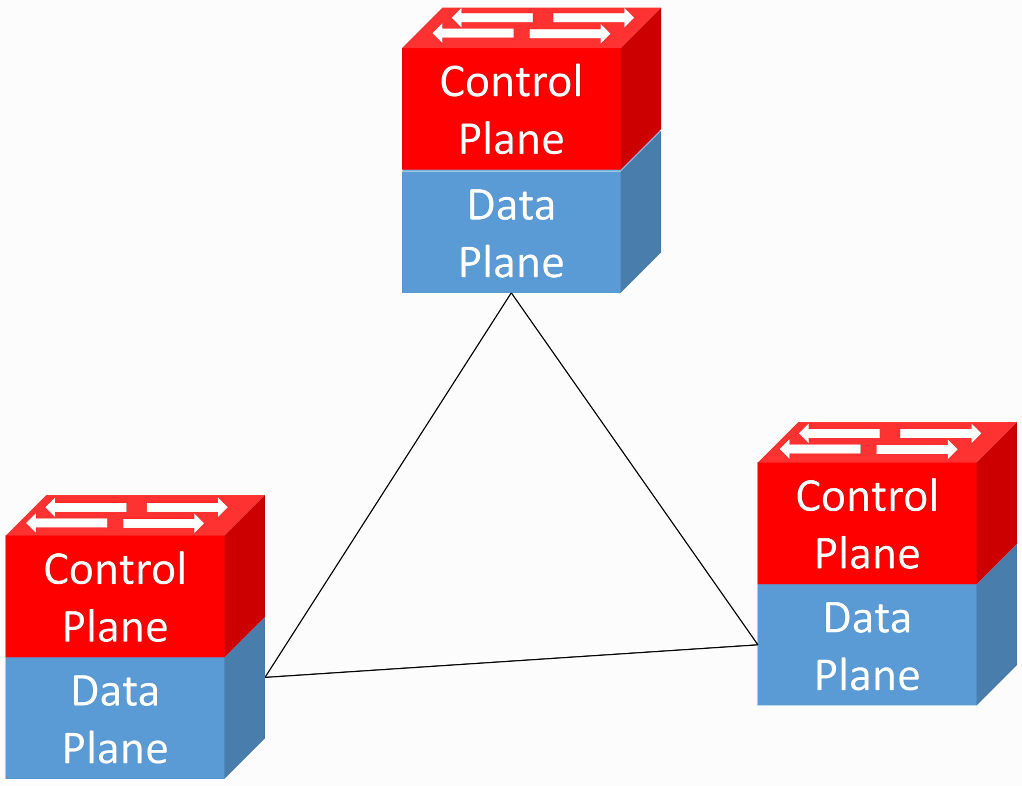
Supervisors

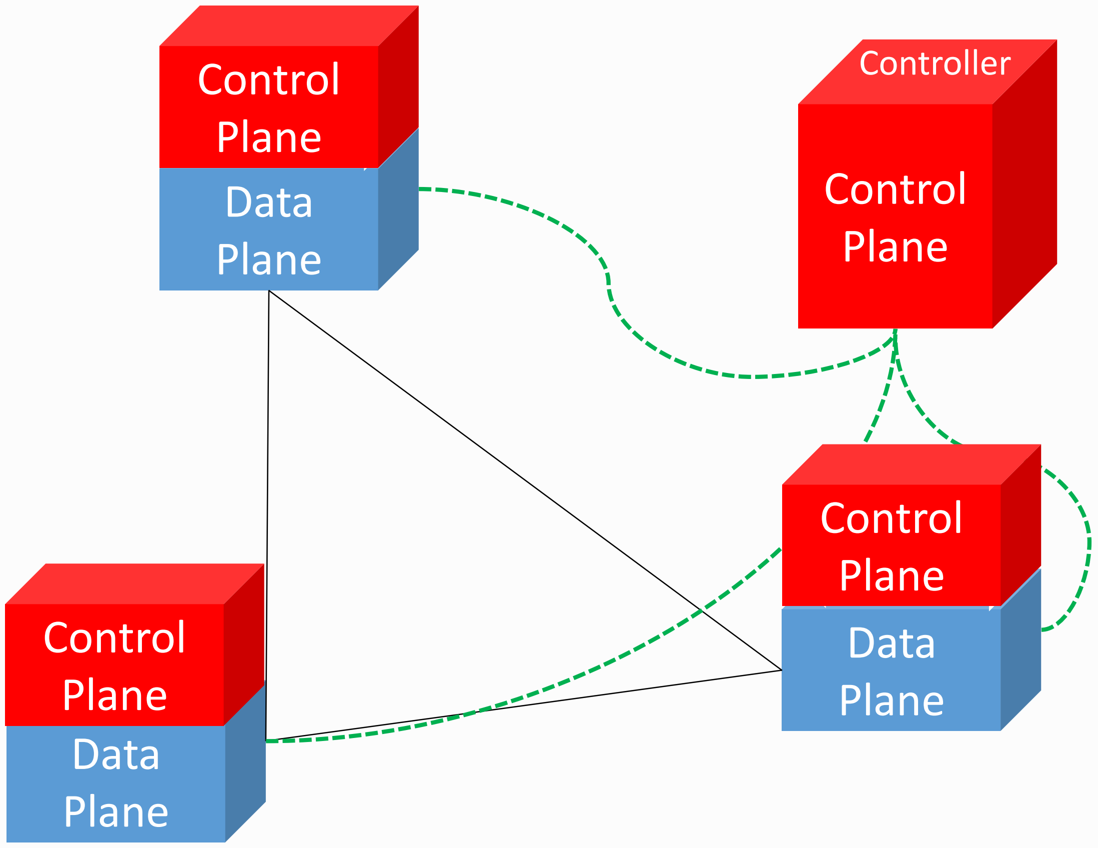
Prof. Pasquale Pace

Prof. Antonio Iera

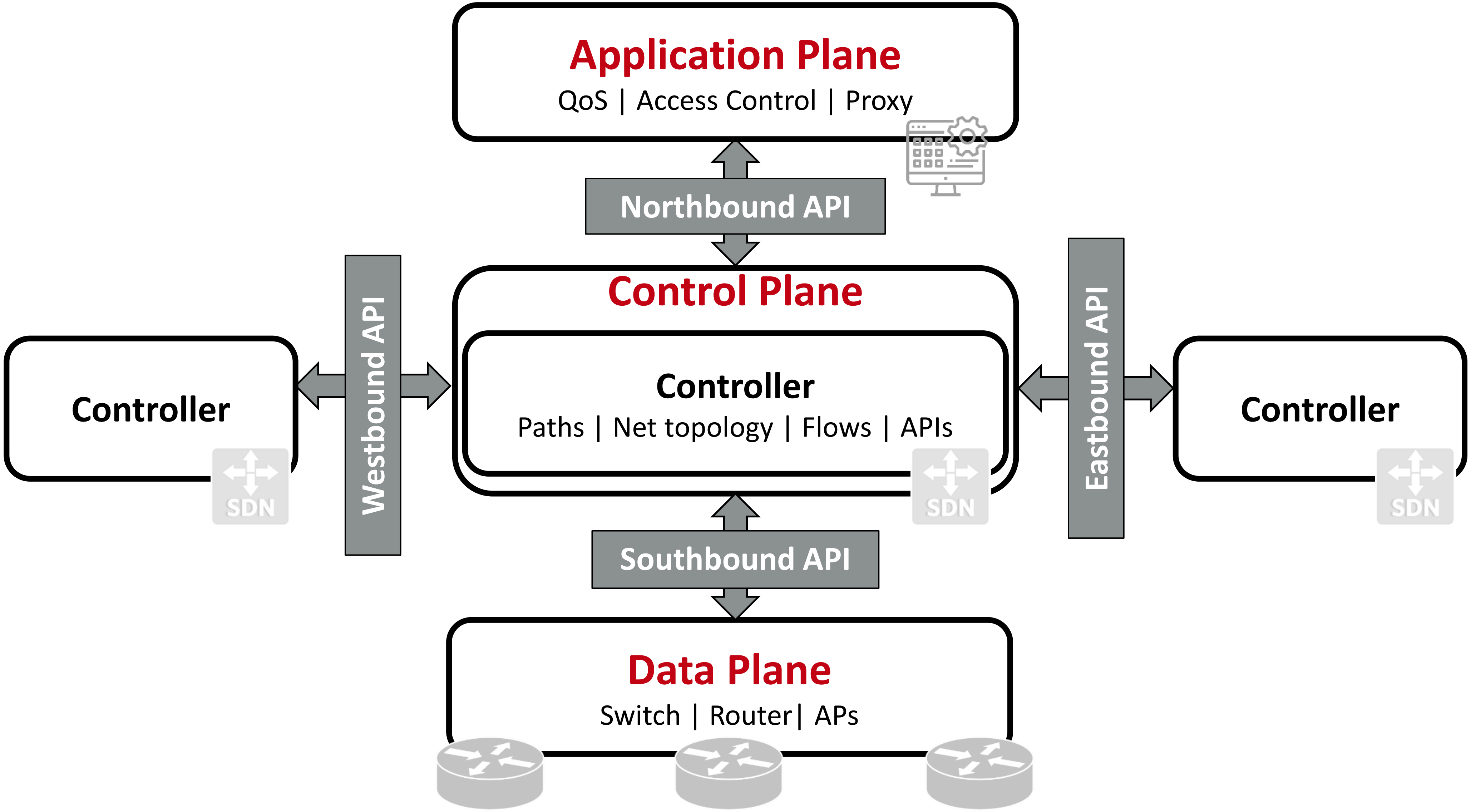
Software Defined Networks (SDN)

Traditional Network	Software Defined Network (SDN)
Data Plane and **Control Plane** in *Network Device*	**Data Plane** in *Network Devices* **Control Plane** centralized in *Controller*

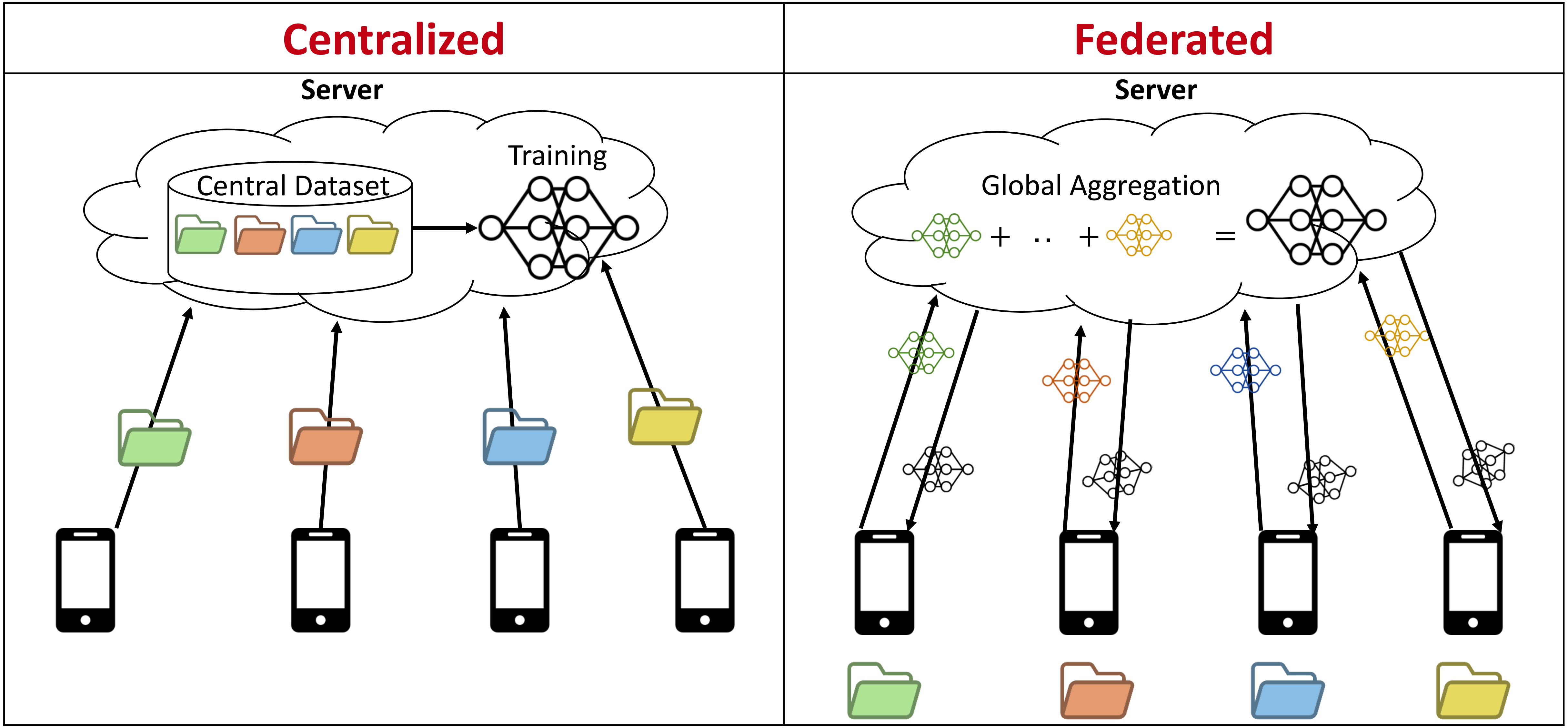




SDN Architecture



Federated Learning (FL)



Existing FL frameworks and proposed enhancements

Most of the literature did not pay attention to the networking aspects of the FL process, which may have a significant performance effects especially for the time-sensitive applications.

The communication resources have usually background data for many applications different to FL that introduce a congestion to the client-server connection. SDN is a promising candidate to handle this issue.

Open Issues

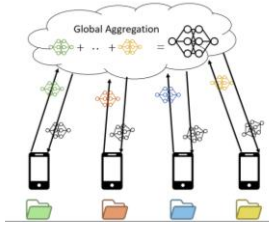
These works have missed the potential cooperation between SDN Controllers and FL servers to dynamically select clients based on their communication resources, link congestion, computational capacity, and memory.

The dynamic nature of the links used to connect FL clients to the FL server introduces challenges due to the lack of a dedicated network for FL.

Dynamic client selection mechanism is necessary to select the most capable clients (CPU, Memory and Communication Resources) round by round, enabling the FL process to be completed as quickly as possible.

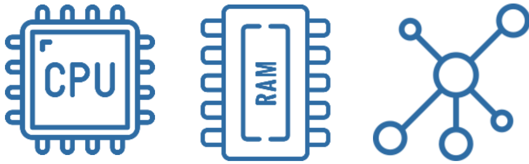
Thesis's Contribution

1. Study the feasibility of introducing SDN in the FL process by dynamically updating routes between FL clients and the FL server based on link congestion.



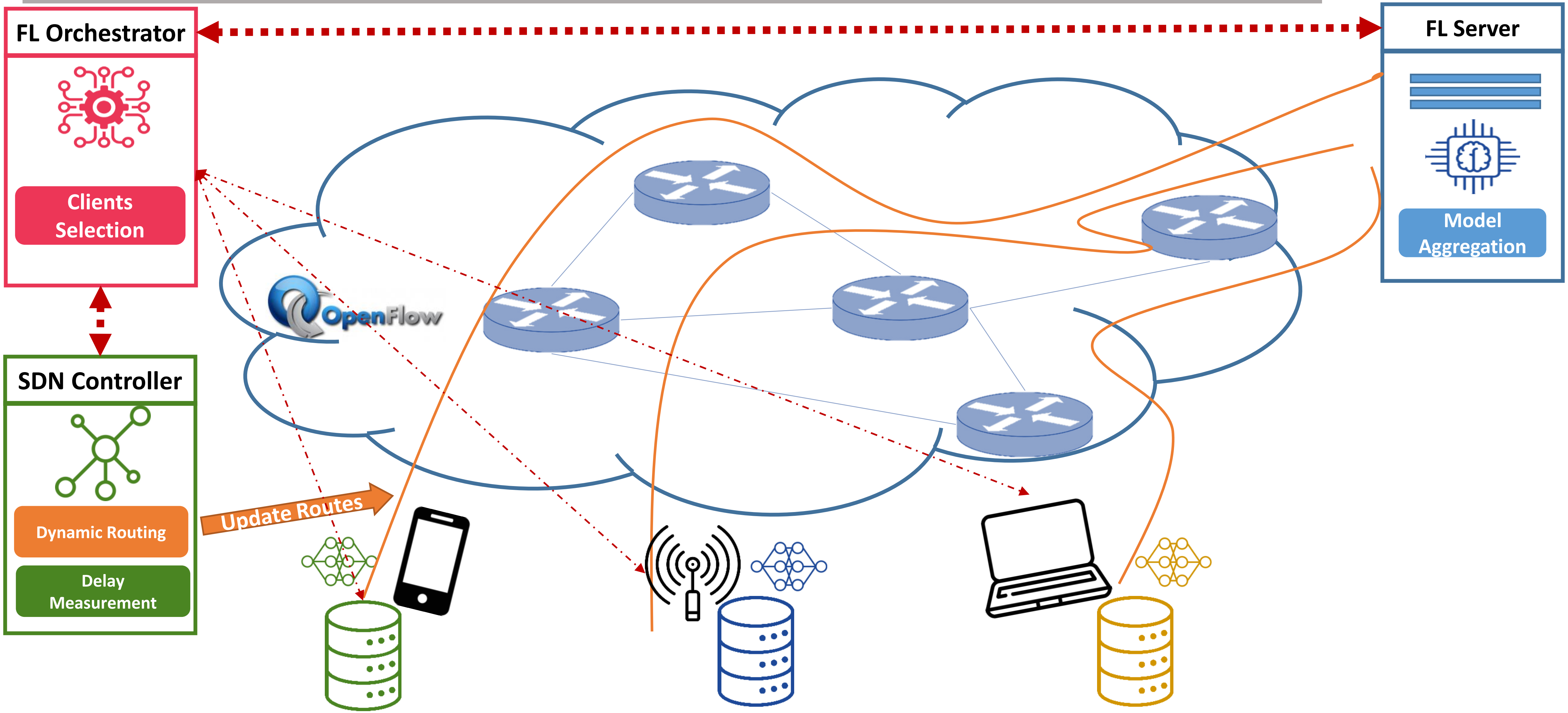
2. Introduce a dynamic client selection mechanism based on the communication resource states between the FL homogeneous clients and FL server.

3. Introduce a dynamic client selection mechanism considering the communication resource states as well as the computational and memory resources of FL heterogeneous clients.

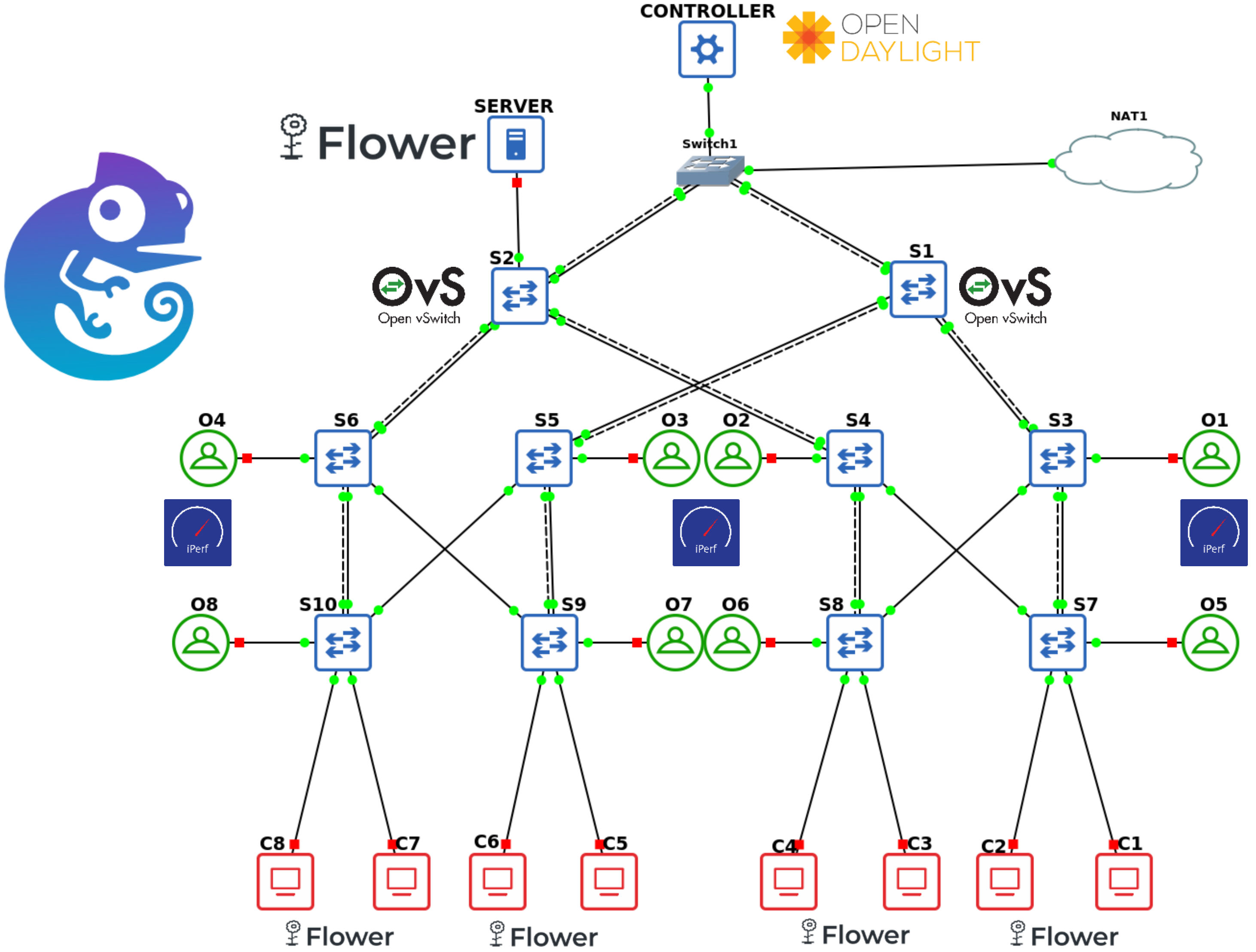


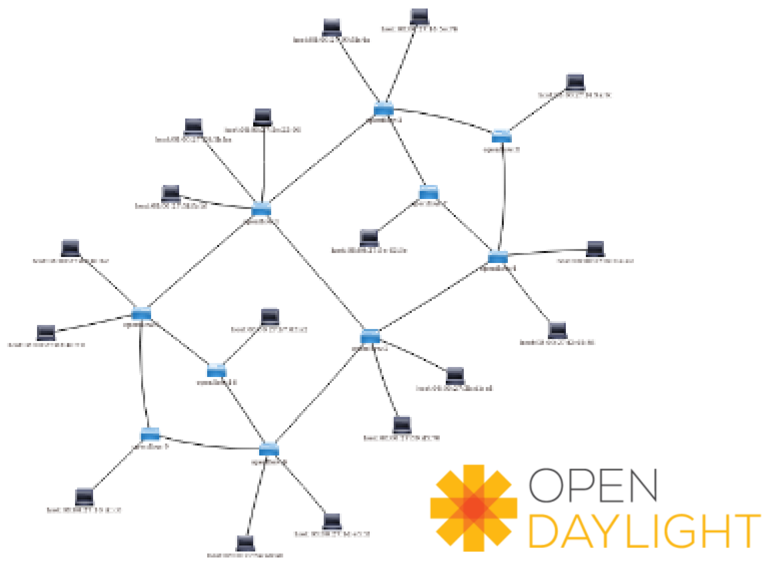
4. Validate the proposed frameworks using a testbed network and compare the results with FL frameworks without the proposed approaches to demonstrate their performance improvements.

Proposed Framework



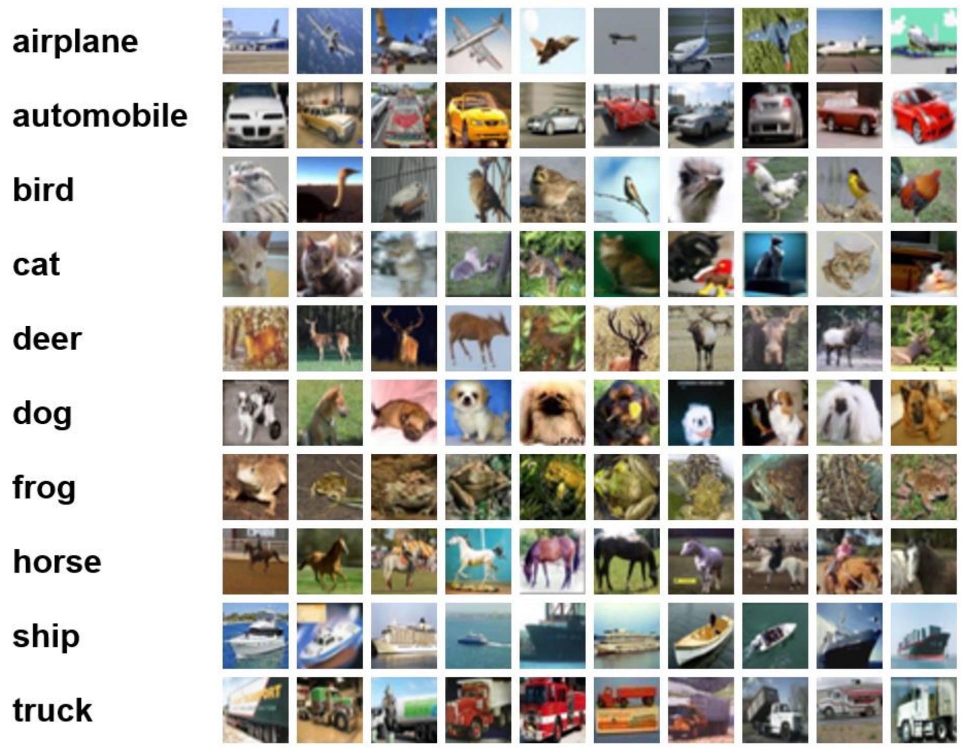
Network Topology and Infrastructure Design



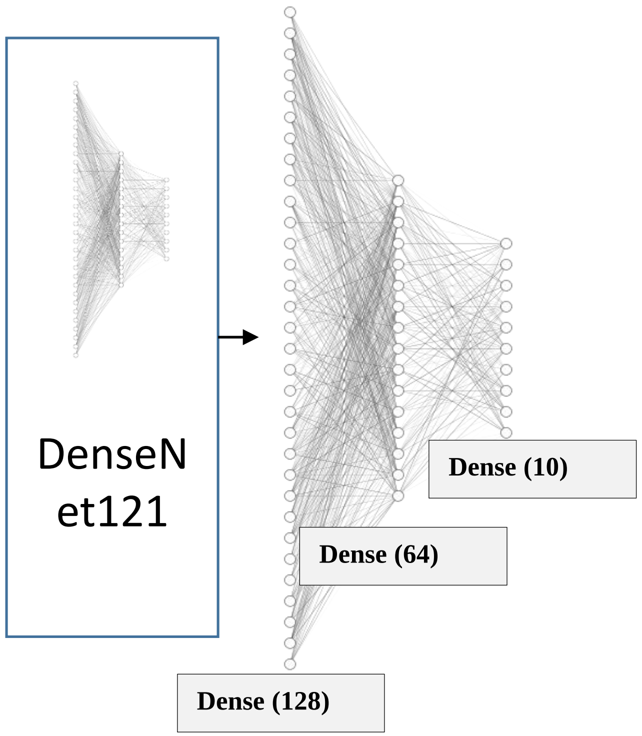


Deep Learning Model & Dataset

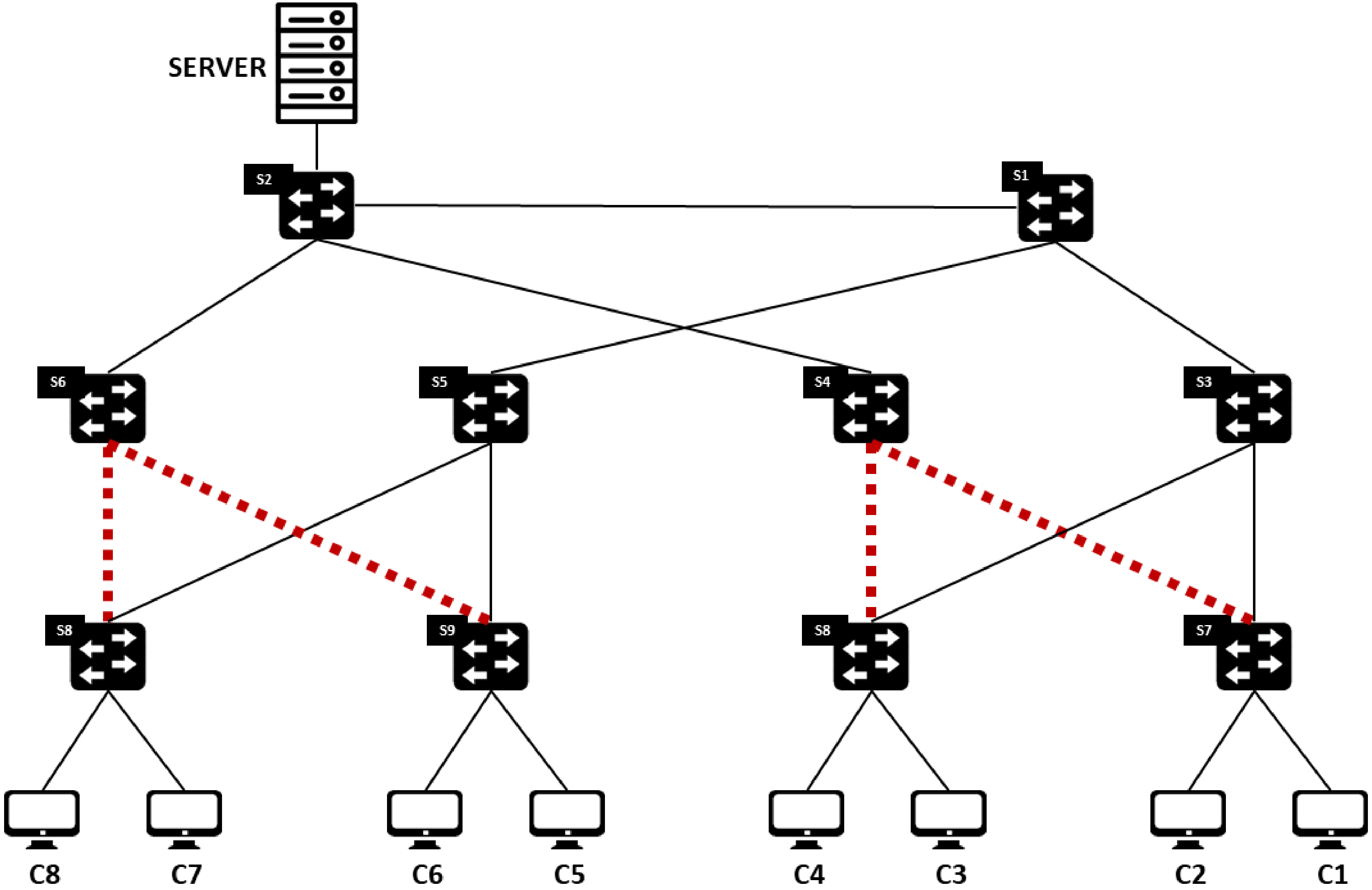
CIFAR10: 10 Classes (6,000 Images per Class)



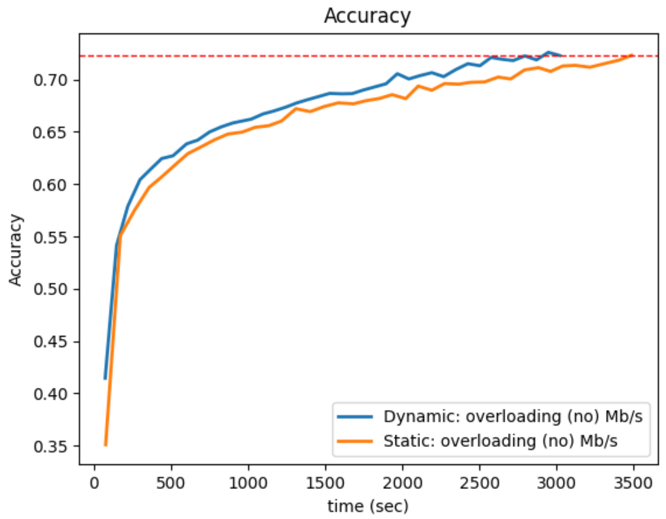
DenseNet121 + 3 Dense Layers 128, 64, 10

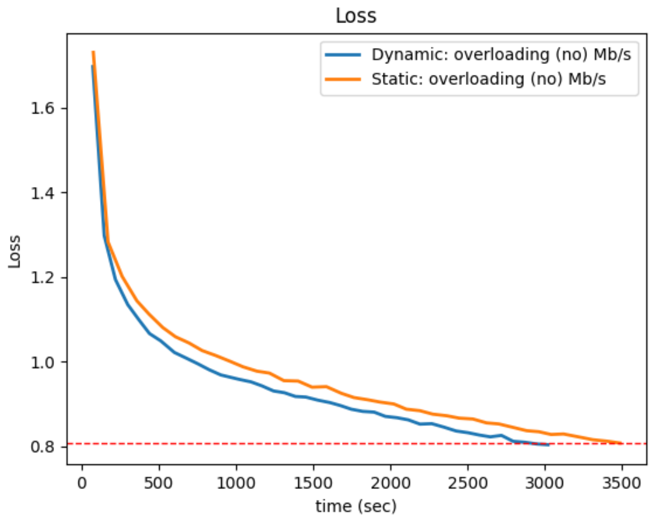


Results and Performance Evaluation
Dynamic Routing



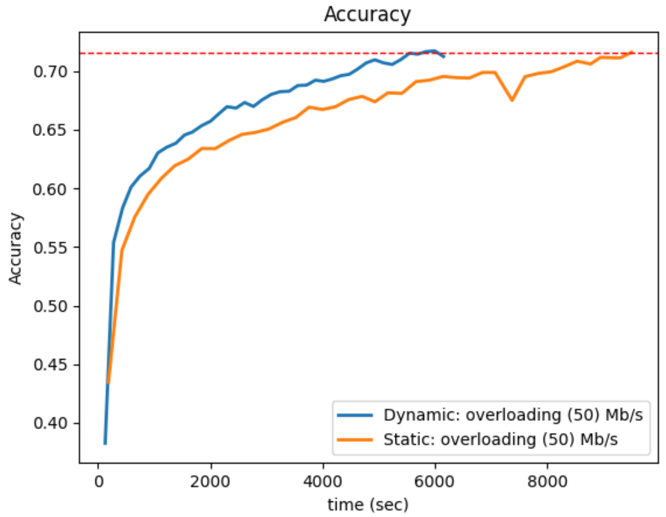
Results and Performance Evaluation
Dynamic Routing

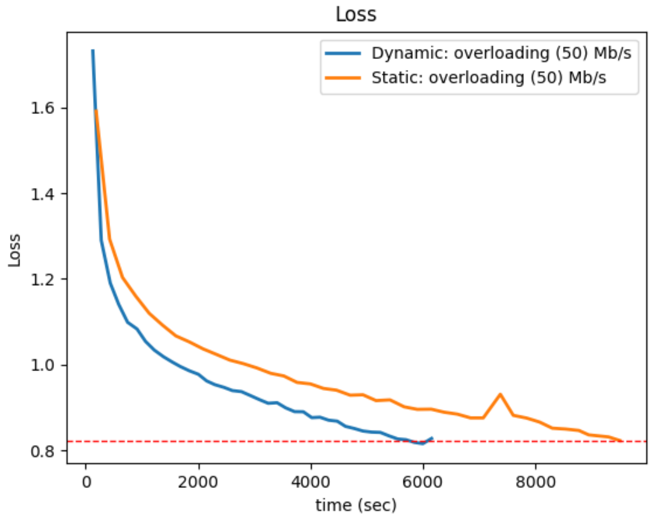




Overload = **0** Mbps

Time Saving = **465.75** sec

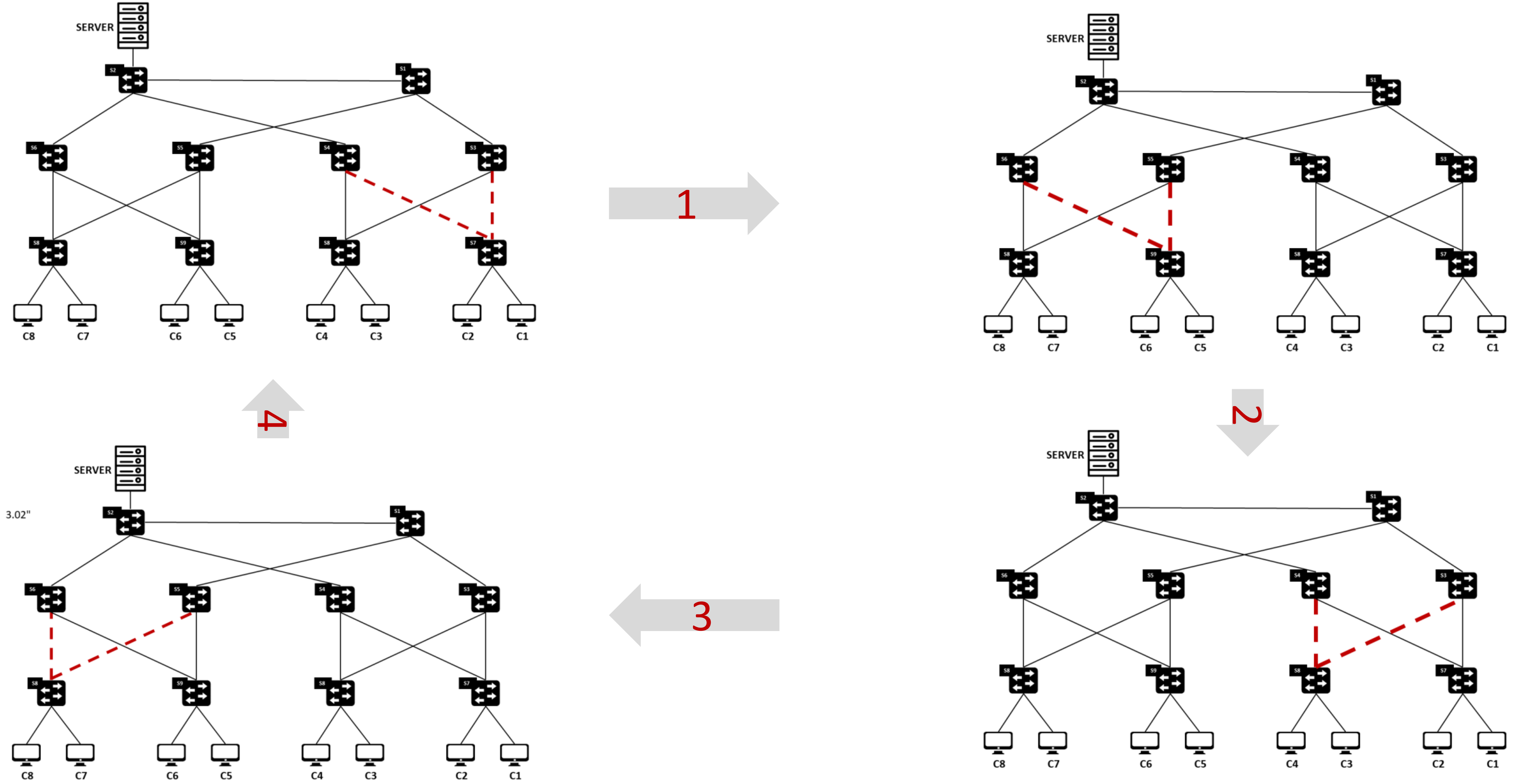




Overload = **50** Mbps

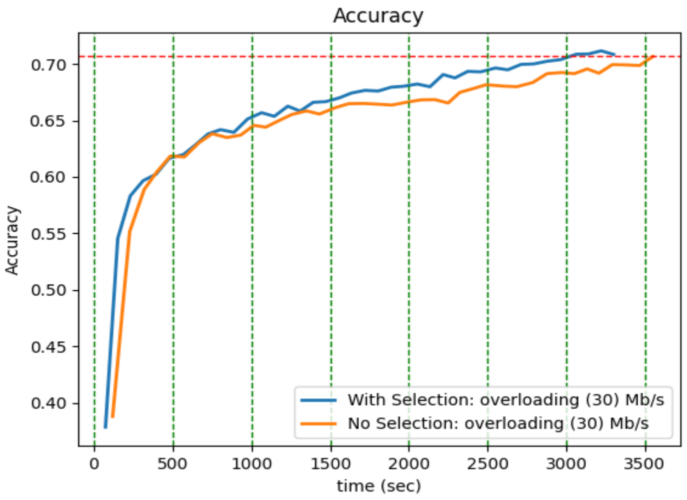
Time Saving = **3346.7** sec

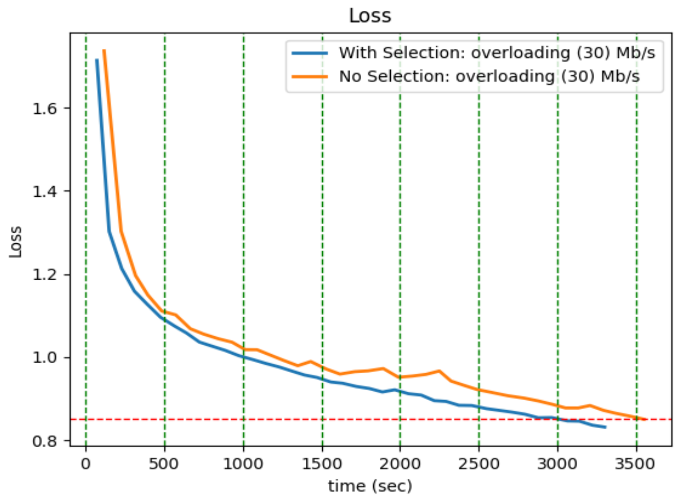
Results and Performance Evaluation
Delay-dependent Client Selection



Results and Performance Evaluation

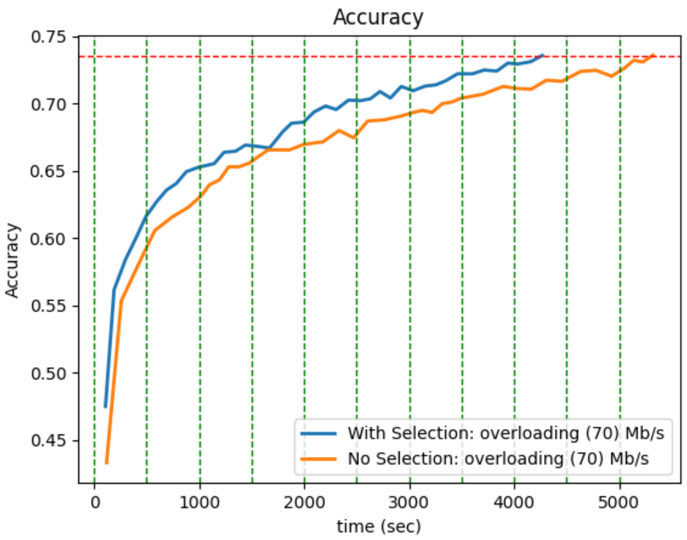
Delay-dependent Client Selection

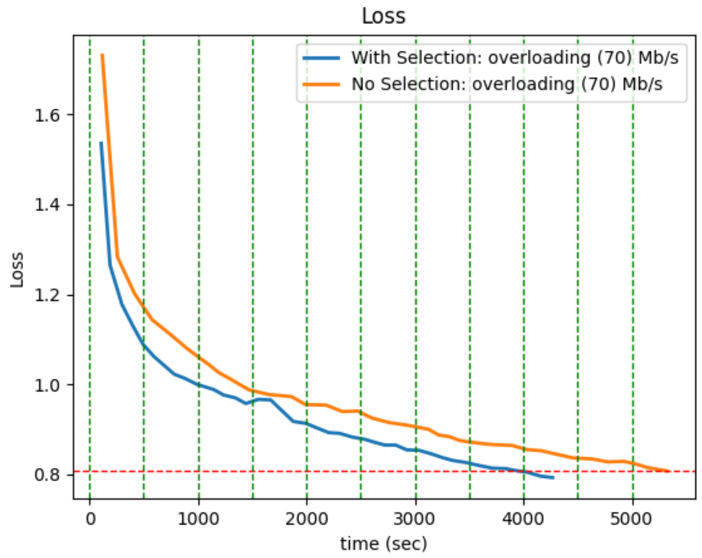




Overload = **30** Mbps

Time Saving = **528.18** sec



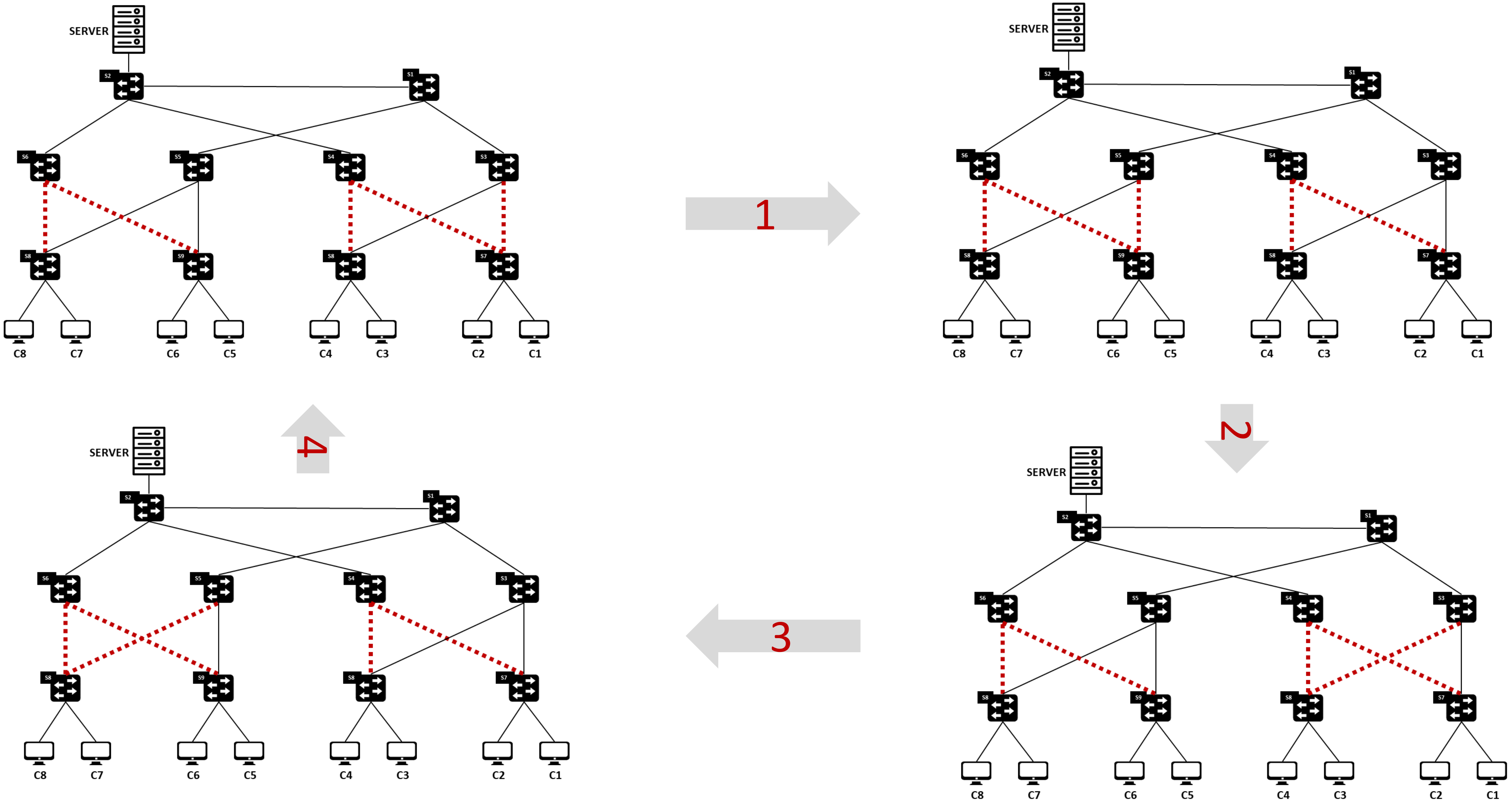


Overload = **70** Mbps

Time Saving = **1049.55** sec

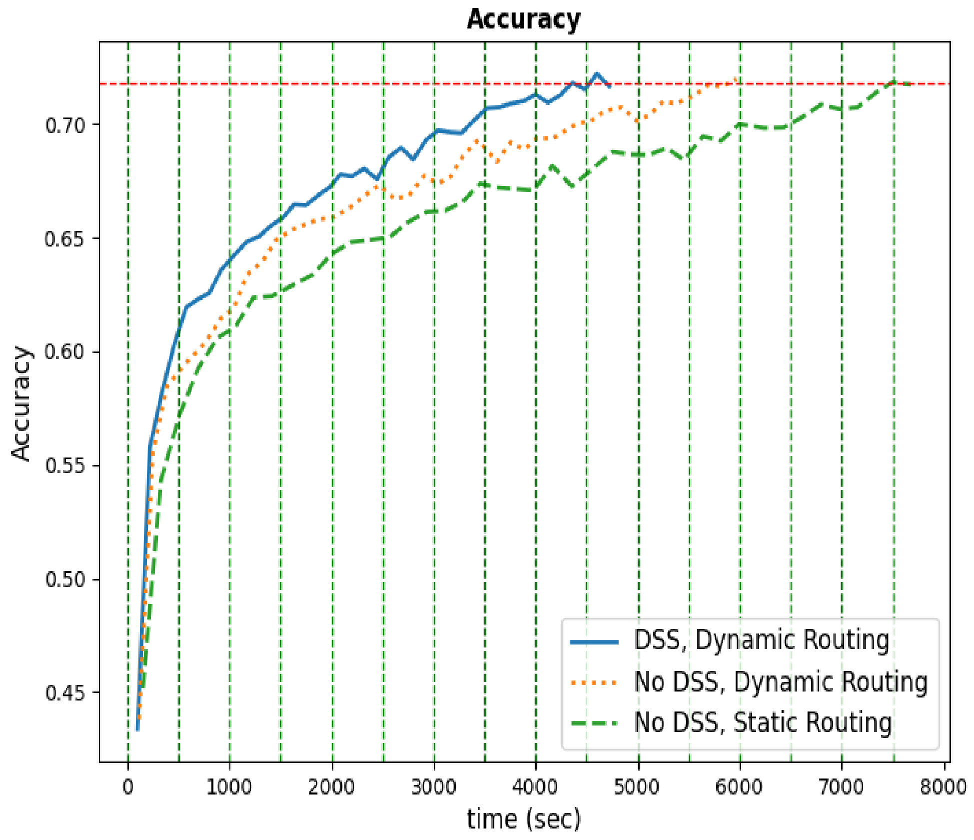
Results and Performance Evaluation

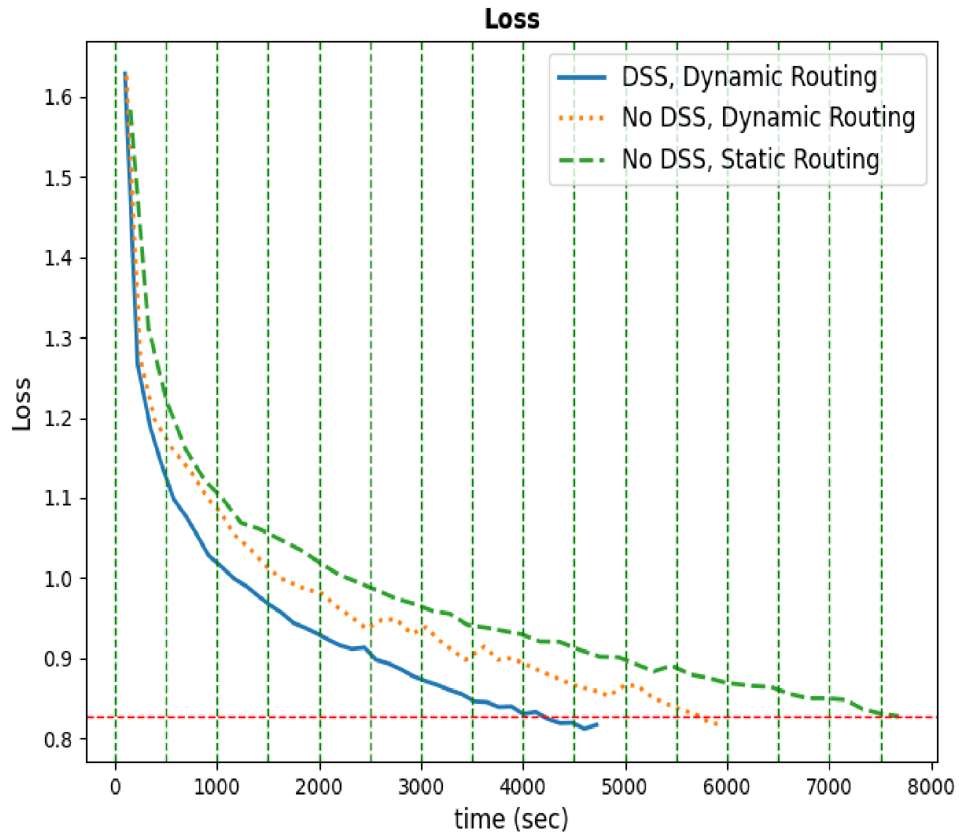
Dynamic Routing + Delay-based Client Selection



Results and Performance Evaluation
Dynamic Routing + Delay-based Client Selection

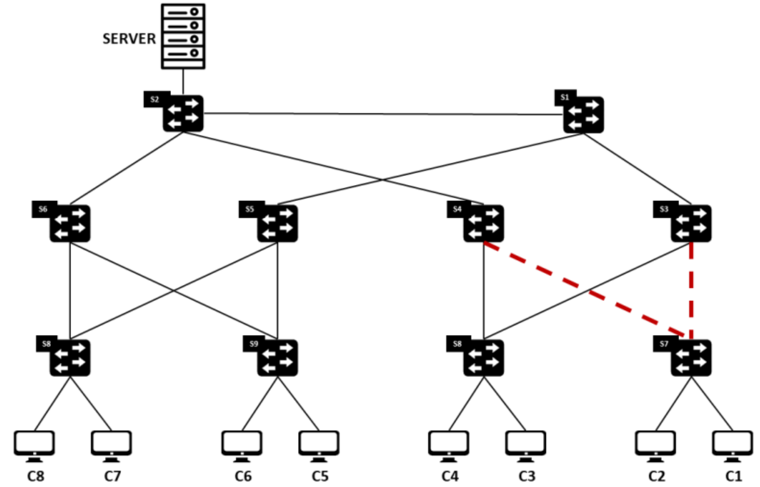
Overload = **25** Mbps



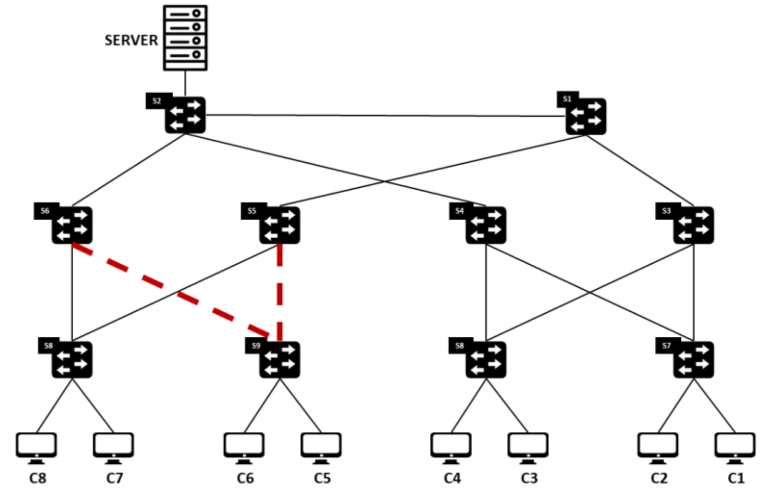


Results and Performance Evaluation

Delay/Computational Resources Client Selection



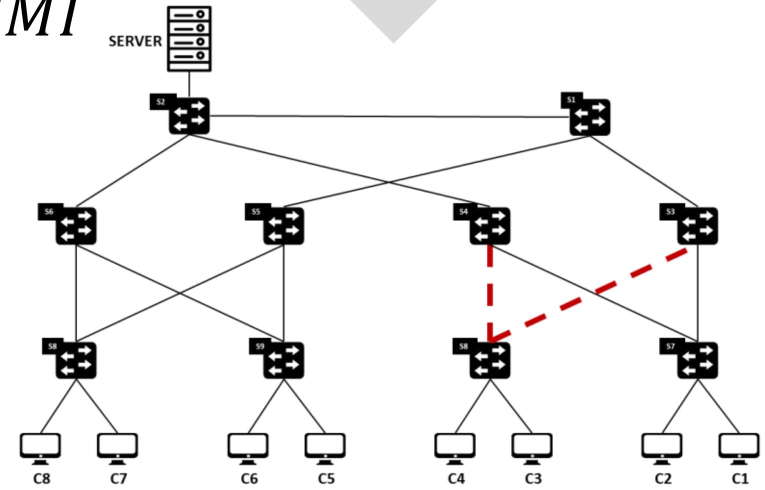
1



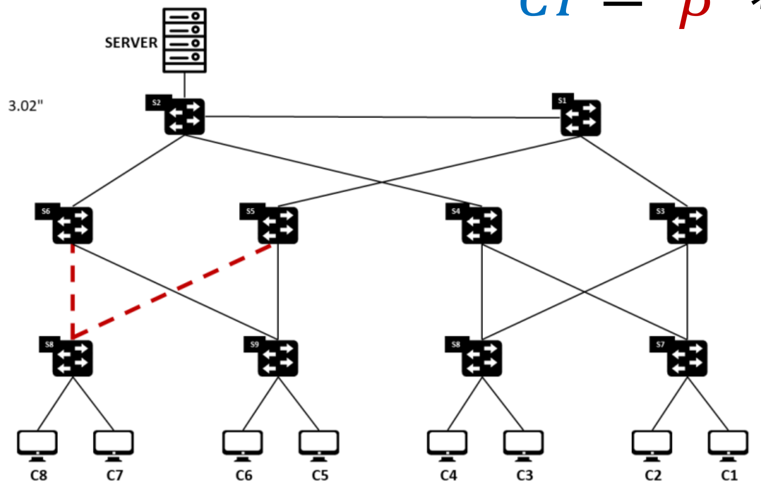
2

$$EI = \alpha * CI + (1 - \alpha) * ND$$

$$CI = \beta * CPUI + (1 - \beta) * MEMI$$



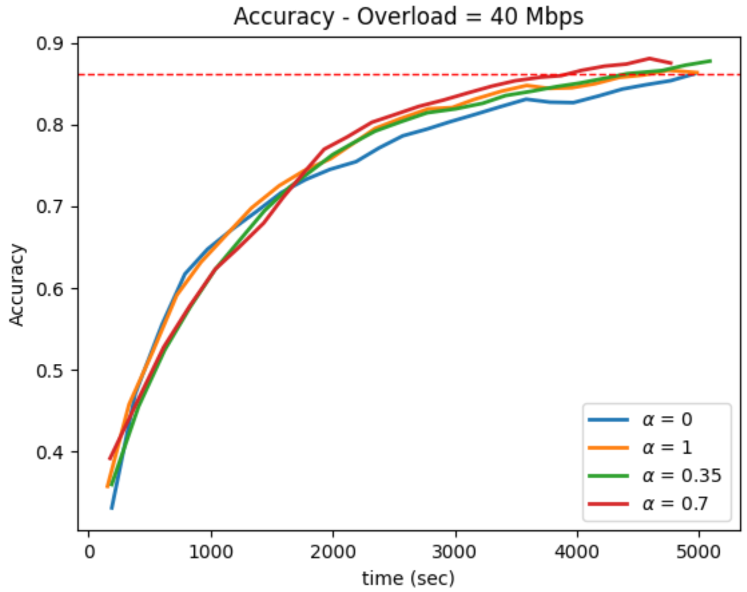
3



4

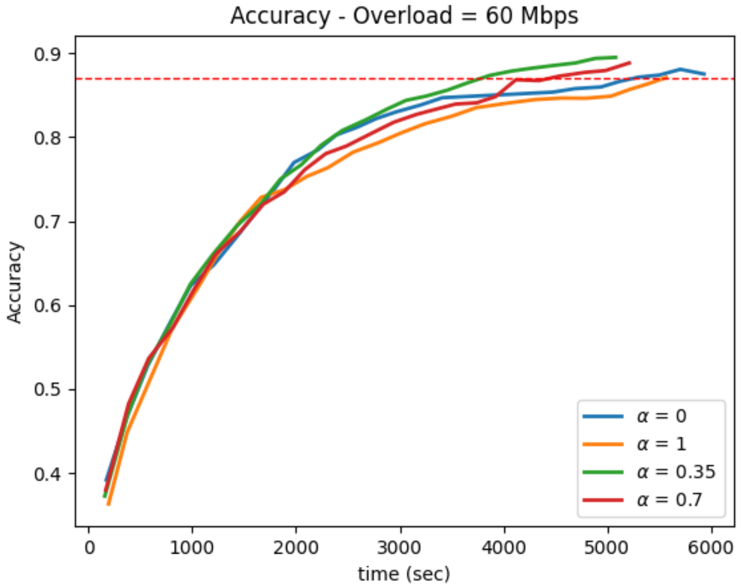
Results and Performance Evaluation
Delay/Computational Resources Client Selection

Overload = **40** Mbps



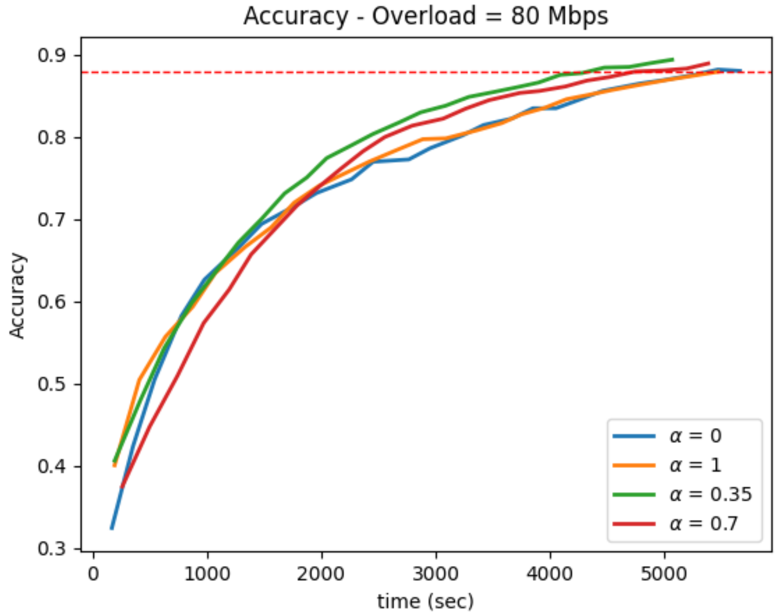
α	Time Saving (sec)
0	*0*
0.35	*558.4336517*
0.7	***1035.40801***
1.0	*366.4758583*

Overload = **60** Mbps



α	Time Saving (sec)
0	*282.6486976*
0.35	***1760.86714***
0.7	*1091.520931*
1.0	*0*

Overload = **80** Mbps



α	Time Saving (sec)
0	*85.04829285*
0.35	***1140.572289***
0.7	*729.876928*
1.0	*0*

Conclusion

- SDN is an efficient candidate to improve the quality of FL in terms of Communication Resources

- Dynamic Routing reduces the convergence time when the network is loaded with other applications' data.
- The reduction is increased with increasing the network load.

- The Delay-based Selection is efficient when all network's clients are homogenous in term of Computational and Memory resources.
- It solves the problem of Dynamic Routing which can not deals with overload when the all available paths are overloaded.
- The reduction is increased with increasing the network load.

- The Delay/Computational Resources Selection is efficient when the network's clients are heterogeneous.
- It solves the problem of Delay-based Selection which can not deals with clients heterogeneity.
- Each Delay and Computational Resources scenario need a specific parameters values (α&β) that need to be optimized (promising solution AI specifically Reinforcement Learning).

Publications

Improving the quality of Federated Learning processes via Software Defined Networking

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Accepted

ABSTRACT

Federated Learning (FL) is rapidly gaining popularity as an effective cooperative and distributed approach, widely used by edge devices, to train machine learning models. Several aspects shall be managed to ensure a FL process that can more precisely match the QoS requirements of the applications that use it. The heterogeneity in the dataset available to each participant in the process, the variability in computational/memory capabilities, and the different availability of communication resources to connect the clients to the server are among the most critical. In this paper we will focus on the latter issue, less investigated in the literature, with particular reference to the case where the FL is used to support time-sensitive applications. Specifically, we will focus on studying the potential of an approach that leverages the Software-Defined Networking paradigm (SDN) to maintain the distributed learning process at high levels of effectiveness and efficiency even in the presence of edge client devices that may be delayed in delivering the result of their training due to the overload conditions experienced in the communication paths to the server. It will be shown, via a proof-of-concept performance evaluation campaign, how the proposed SDN support to the FL can guarantee significant overall reductions in process time at the cost of limited signaling overhead due to traffic to and from the controller.

CCS CONCEPTS

• Networks → Network architectures; Network performance evaluation; • Computing methodologies → Machine learning.

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1 INTRODUCTION

Recently a plethora of applications are emerging that are based on the use of machine learning techniques to support increasingly sophisticated tasks to be carried out in different vertical markets [1], such as Industry 4.0, e-Health, Automotive, etc. The involvement in these services of different devices distributed on the edge of emerging network platforms and the growing need to maintain strict privacy on user data have made the so-called Federated Learning (FL) approach increasingly interesting [2]. Indeed, the latter is based on training a Machine Learning (ML) algorithm on multiple decentralized edge devices that maintain data samples locally, without exchanging them across the network.

Unfortunately, a problem that goes hand in hand with the numerous advantages of Federated Learning (and distributed learning techniques, more generally) is undoubtedly the fact that very heterogeneous devices in terms of computational capacity, amount of memory and communication resources can take part in this distributed learning process, some of which could also be Internet of Things (IoT) devices and therefore constrained by their nature.

SDN-Assisted Client Selection to Enhance the Quality of Federated Learning Processes

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UNDER REVIEW

***Abstract*—An emerging modality, increasingly used by edge devices, to train machine learning models in a distributed and cooperative way is Federated Learning (FL). It combines an increase in the quality of the learning process with data privacy needs. Alongside the advantages of this emerging paradigm, however, there is a critical factor that risks seriously affecting its effectiveness in future 5G and 6G application scenarios: the possible delays deriving from the scarcity of communication resources to connect the clients to the server, which risks slowing down the process excessively and making it less effective in the presence of new types of real-time applications typical of 5G/6G scenarios. To face this issue, the paper proposes a new approach to client selection that, unlike the various approaches to streamlining FL communications proposed so far, starts from a typically networking research point of view and makes use of the potential of the Software-Defined Networking (SDN) paradigm for the choice and continuous dynamic update of the clients participating in the FL process. This allows to keep the distributed learning process at high levels of effectiveness and efficiency, i.e., guaranteeing an overall time reduction of the FL process under different network traffic load conditions, as demonstrated by the performance evaluation campaign conducted through the implementation of a testbed platform.**

***Index Terms*—SDN for AI, Federated Learning, FL client selection, SDN-based orchestration.**

I. INTRODUCTION

Initially proposed by Google [1], FL is rapidly emerging as a distributed paradigm capable of attracting significant interest in several vertical markets to support intelligent pervasive applications in many domains of everyday life. Interest in FL ...

one of the most promising solutions to fulfill 6G's vision of ubiquitous AI [3], [4].

An issue that may affect the FL process is the possibility that the scarcity of resources in the network that the traffic of the various clients has to cross, negatively influences the overall achievable performance. This does not represent a problem in cases of support for typical IoT applications in which FL is intended for a high number of mobile and/or constrained IoT devices in which losses and delays in the various update rounds are already expected. The same can be said for several long-term applications that exploit FL for example to make predictions in the field of e-Health or in the environmental field. However, if we place ourselves in an evolutionary context in which several of the typical applications that users will want to use through future 5G/6G platforms are expected to be time sensitive, then the situation changes radically and a reduction of the delay in the learning process becomes mandatory.

The problem of making communications more efficient in the FL process is not new and has already been addressed in the literature, but the vast majority are research and proposals that come from the scientific communities of Learning and aim at adapting the process to streamline the transfer of model parameters between client and server.

In this paper, the proposed approach starts from the very recent literature dealing with the topic of the *"Network for AI"* (as opposed to the more traditional approach of "AI for ...

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Thank You For Your Kind Attention

Ahmad Mahmod