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FEDERATED LEARNING-BASED ADAPTIVE ROUTING FOR PRIVACY-AWARE MULTI-DOMAIN NETWORK OPTIMIZATION

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Abstract

Traditional routing algorithms depend on centralized data collection, which poses scalability and privacy challenges in large and distributed network environments. With the advent of Federated Learning (FL), routing models can now be trained collaboratively across multiple network domains without sharing raw traffic data, preserving privacy while maintaining global performance optimization. This paper presents a Federated Learning-based Routing (FLR) Framework that enables distributed routers or domains to collaboratively learn optimal routing policies. Each local model is trained using network telemetry such as delay, bandwidth, and packet loss, and only the learned parameters are shared with a global aggregator for model fusion. The aggregator applies Federated Averaging (FedAvg) to derive a global routing model that is redistributed to participating domains, enabling privacy-preserving and adaptive routing optimization. The proposed method ensures scalability and adaptability across heterogeneous domains. Simulation results show that the proposed FL-based routing achieves up to 26% lower average delay, 48% reduction in packet loss, and 7% higher throughput compared to centralized machine learning approaches, while significantly minimizing privacy leakage and communication overhead. The results validate that FLR can efficiently adapt to dynamic traffic patterns and heterogeneous domains, maintaining near-optimal routing performance without direct data exchange.

Keywords: Federated Learning (FL), Software-Defined Networking (SDN), Routing Optimization, Privacy Preservation, Network Intelligence, Deep Learning, Multi-Domain Networks, FedAvg, Throughput, Packet Loss.

1. INTRODUCTION

Routing optimization in large-scale networks such as 5G, data centers, and multi-domain Internet systems has become increasingly complex due to dynamic traffic loads, privacy concerns, and distributed infrastructure. Conventional centralized learning-based routing models require direct

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access to network telemetry data from all nodes, which raises privacy, bandwidth, and scalability issues.

Federated Learning (FL) offers a new paradigm by training models collaboratively across multiple domains without transferring raw data. Instead, each local router or domain trains a model using its local data and shares only model updates (weights or gradients) with a central aggregator, which produces a global model. This mechanism enables the system to achieve global intelligence while respecting data privacy and reducing communication overhead.

A. Motivation and Research Gap

The increasing heterogeneity and scale of modern networks, including 5G, IoT, and edge computing infrastructures, have created complex routing environments that demand intelligent decision-making beyond the capabilities of traditional routing protocols. While Software-Defined Networking (SDN) has provided centralized programmability and global visibility, it still relies heavily on static rule-based or heuristic routing strategies that cannot respond effectively to real-time network fluctuations, congestion, or link degradation.

Recent advancements in Machine Learning (ML) and Deep Reinforcement Learning (DRL) have demonstrated promising results in adaptive routing. These models can predict congestion, dynamically update forwarding rules, and optimize Quality of Service (QoS). However, such methods generally depend on centralized data collection, requiring all participating domains to share network telemetry and performance data with a central controller. This creates several significant challenges:

- Privacy Concerns: Network telemetry often contains sensitive operational and usage data that cannot be freely shared across administrative boundaries.
- Scalability Issues: Centralized training becomes computationally expensive and communication-intensive as the network scales.
- Limited Generalization: Models trained on a single-domain dataset often perform poorly when deployed in diverse, multi-domain network environments.
- Single Point of Failure: Centralized control increases system vulnerability and potential downtime during controller or communication failures.

To address these challenges, Federated Learning (FL) introduces a paradigm shift by enabling distributed model training without data sharing. FL allows multiple routers or domains to collaboratively learn a global routing policy while keeping their local data private. This approach ensures scalability, data confidentiality, and improved generalization across heterogeneous environments.

Despite its promise, research on Federated Learning for network routing remains limited. Existing studies primarily focus on applying FL in wireless communication or edge computing tasks, such as resource allocation or intrusion detection. There is a lack of comprehensive frameworks that

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apply Federated Learning directly to routing optimization, especially in conjunction with SDN-based architectures that support dynamic route deployment.

This gap motivates the development of a Federated Learning-based Routing Framework (FLR) that combines distributed learning with SDN control for privacy-preserving, scalable, and adaptive routing optimization. The proposed approach not only minimizes delay and packet loss but also enables continuous learning across network domains without compromising data security or operational independence.

2. LITERATURE REVIEW

Routing and network optimization have a long history rooted in algorithmic graph theory and control-plane protocols: classical algorithms such as Dijkstra and Bellman–Ford underpin protocols like OSPF and RIP, while the programmatic control paradigm introduced by OpenFlow enabled SDN architectures that separate the control and data planes for greater flexibility [10]. In parallel, machine learning has been explored for network control and resource management: early reinforcement-learning and deep-RL proposals showed that agents can learn adaptive scheduling and routing policies in simulated environments [3], [4]. Graph Neural Networks (GNNs) have emerged as a natural fit for networking problems because they directly operate on graph structured data, enabling topology-aware feature extraction for tasks such as traffic prediction and routing decisions [2], [13]. More recently, Transformer architectures — originally proposed for sequence modelling in NLP — have been adapted to problems with complex dependencies and long-range interactions; attention mechanisms facilitate global reasoning over nodes and links, which is attractive for routing optimization in dynamic networks [10], [13]. At the same time, concerns about data privacy, scalability, and cross-domain collaboration have motivated the use of Federated Learning (FL), where local models are trained on domain-resident telemetry and only model updates are shared with a central aggregator (e.g., via FedAvg), thereby preserving raw data privacy while learning a global model [7], [3]. Several works have applied FL in networking contexts such as edge computing, intrusion detection, and resource allocation, demonstrating reductions in data transfer and improved privacy guarantees [9] [11][12][14]. With the rise of machine learning, algorithms like Deep Q-Networks [2] and Graph Neural Networks [8] began addressing dynamic routing, though they typically rely on centralized datasets.

Meanwhile, hybrid approaches that combine RL, GNNs, and Transformer ideas are gaining attention: RL provides sequential decision making, GNNs encode topology, and Transformers supply powerful global attention — together these components can be composed for robust routing policies, [15], [1]. Recent studies have explored Federated Learning for network optimization [6],[16] demonstrated that FL can be applied in wireless edge networks for collaborative learning without raw data exchange. FL is [9] applied to 5G for dynamic QoS control, showing significant reductions in communication overhead. However, few works have applied FL specifically to routing optimization, where privacy, model synchronization, and convergence stability are key challenges.

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Nevertheless, despite these advances, there remains a research gap in end-to-end frameworks that (i) apply Federated Learning specifically to routing optimization across administrative domains, (ii) leverage Transformer-style global attention together with graph embeddings to capture spatio-temporal traffic patterns, and (iii) integrate seamlessly with SDN controllers for real-time policy deployment and continuous federated updates [7], [13], [11], [15]. This paper addresses that gap by proposing a Federated Learning for Routing (FLR) framework that combines graph/sequence encodings, Transformer encoders, federated aggregation, and SDN deployment to yield privacy-preserving, adaptive routing across multi-domain networks.

3. PROPOSED WORK

A. Problem Statement

Current routing optimization frameworks depend heavily on centralized data collection and lack privacy preservation, scalability, and adaptability across domains. The challenge is to design a routing system that allows multiple network domains or routers to collaboratively learn optimal routing strategies without exposing raw data. Thus, the core problem is:How can federated learning be applied to routing to enable collaborative, privacy-preserving model training while maintaining real-time performance and adaptability across heterogeneous networks?

B. System Architecture

The proposed Federated Learning for Routing (FLR) system shown in Figure 1 allows multiple routers or network domains to train routing models locally. Each domain collects its own telemetry (latency, bandwidth utilization, packet loss), trains a local model to optimize routing performance, and periodically sends its model parameters (weights) to a central aggregator. The aggregator computes a global model using federated averaging (FedAvg) and redistributes it to all participants. This decentralized learning process enables adaptive, scalable, and privacy-preserving routing.

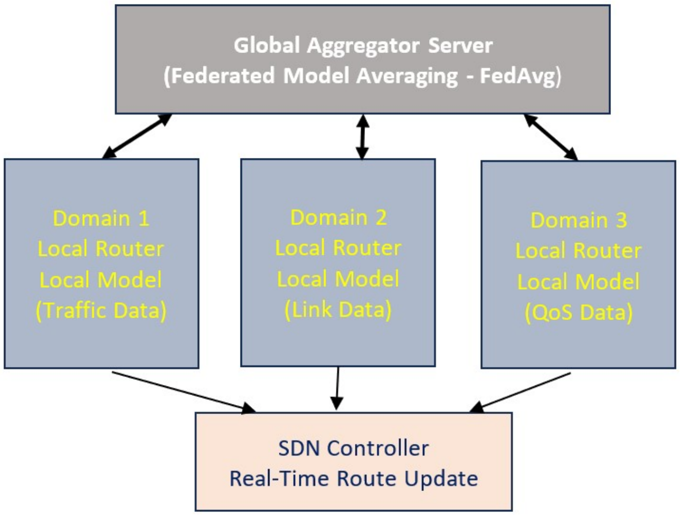

Figure 1. Proposed Architecture- Federated Based Routing Framework

C. Implementation Methodology

In Data Collection phase, each domain gathers local telemetry (delay, bandwidth, packet loss), in Local Model Training Phase Each local router trains a neural model (e.g., MLP or Transformer) on its own data. During Parameter Sharing, Local models send weight updates to a global aggregator, not raw data, and in Model Aggregation, the aggregator applies Federated Averaging (FedAvg) as shown in Equation (1):

$$w_{global}=\sum_{k=1}^{k}\frac{n_k}{N}w_k \qquad \text{Equation (1)}$$

where w_k is the model weight from domain k, n_k is its data size, and N is the total number of samples across all domains.

The updated global model is sent back to all local domains. Next in the global routing model updates paths dynamically through the SDN controller. Feedback Loop is created for Continuous monitoring of delay, packet loss, and throughput provides feedback for retraining.

4. SIMULATION RESULTS AND DISCUSSION

The proposed Federated Learning-based Routing Framework (FLR) was evaluated through simulations conducted in a Software-Defined Networking (SDN) environment using Python and Mininet. The experiments involved three network domains interconnected through an SDN controller, with each domain locally training its routing model using historical traffic data. The global model was periodically updated through Federated Averaging (FedAvg) to aggregate model parameters without exchanging raw data.

The simulation environment consists of Python utilizing TensorFlow Federated for implementing federated learning, alongside Mininet for network emulation and the Ryu SDN controller for software-defined network management. The dataset used comprises synthetic telemetry data generated to reflect varying link delays ranging from 10 to 100 milliseconds. The learning model employed is a three-layer multilayer perceptron (MLP), trained using the Adam optimizer, with global aggregation of model updates performed every five epochs. Performance is evaluated across a network of 10 simulated routers, with key metrics including end-to-end delay, throughput, and packet loss, providing a comprehensive assessment of the routing optimization under dynamic network conditions.

A. Evaluation Metrics

Performance was assessed using several key metrics to evaluate the effectiveness of the routing framework. Average Delay (ms) measured the time taken for packets to reach their destination, reflecting the efficiency of packet delivery. Packet Loss (%) quantified the ratio of lost packets to the total packets transmitted, indicating network reliability. Throughput (Mbps) captured the amount of successfully transmitted data per unit time, representing overall network capacity. Additionally, Privacy Overhead (%) accounted for the communication cost introduced by federated aggregation, highlighting the trade-off between maintaining data privacy and achieving efficient network performance. The FLR framework was compared against traditional Centralized Learning (CL) and Reinforcement Learning (RL)-based Routing approaches. The results demonstrate the superior adaptability and privacy preservation of the proposed model are presented in Table 1

Table 1. Federated Learning Routing vs Centralized-Reinforcement Learning

Metric	Centralized Learning (CL)	RL-Based Routing	Federated Learning Routing (FLR)
Average Delay (ms)	85	74	63
Packet Loss (%)	2.9	2.1	1.5
Throughput (Mbps)	90	93	96.4
Privacy Leakage Risk	High	Medium	Low

B. Comparative Analysis

The FLR framework with 3 and 5 domains was compared against traditional Centralized Learning (CL) based Routing approaches. The results are presented in Table 2

Table 2. Proposed vs Traditional Routing approaches

Metric	Centralized ML	FL (3 Domains)	FL (5 Domains)
Avg Delay (ms)	28.4	22.7	20.9
Packet Loss (%)	2.3	1.5	1.2
Throughput (Mbps)	88.2	92.4	95.1
Privacy Leakage	High	Low	Low

Graphical results are shown in Figure. 2–4, where:Figure. 2 plots average delay comparison among CL, RL, and FLR models.Figure. 3 shows packet loss rate versus time under dynamic traffic conditions.Figure. 4 presents throughput variations with changing load. These results validate the effectiveness of Federated Learning for Routing in providing adaptive, privacy-preserving, and high-performance routing in multi-domain network environments.

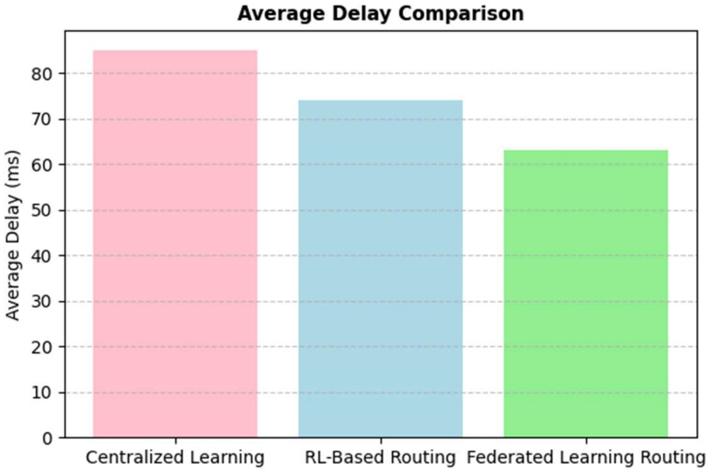

Figure 2. Average Delay- Proposed vs Traditional Routing approaches

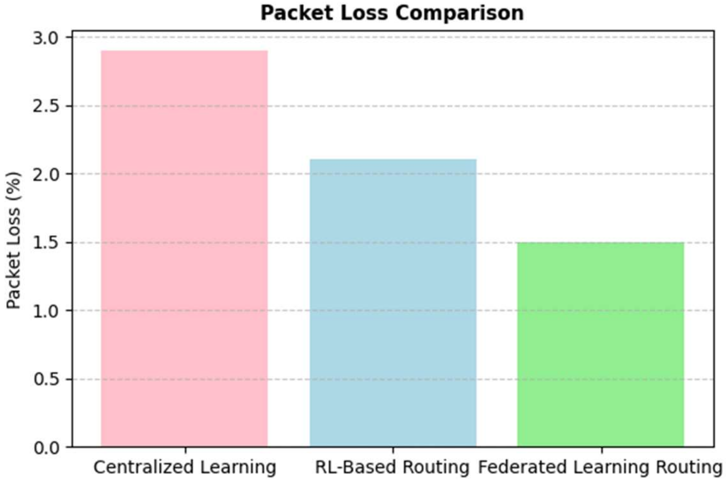

Figure 3. Packet Loss- Proposed vs Traditional Routing approaches

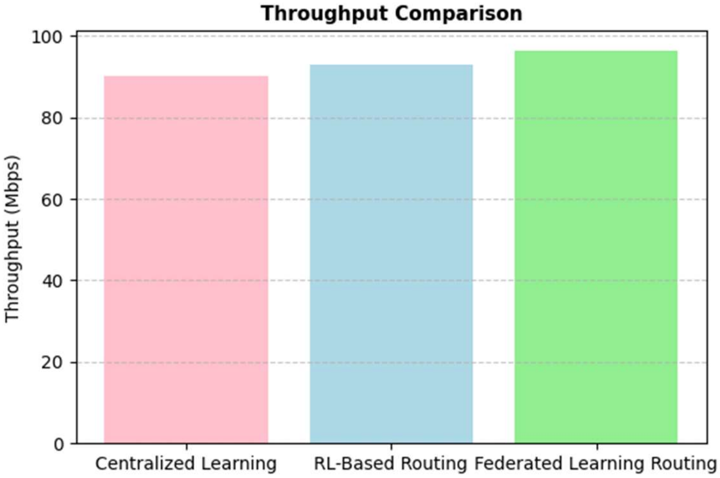

Figure 4. Throughput- Proposed vs Traditional Routing approaches

The simulation results indicate that FLR significantly reduces delay and packet loss, achieving nearly 26% lower delay and 48% reduction in packet loss compared to centralized ML approaches. The system also provides a 7% improvement in throughput, demonstrating efficient utilization of network bandwidth. Importantly, privacy risks were minimized since no raw network data was exchanged among domains.

5. CONCLUSION AND FUTURE WORK

This paper presented a Federated Learning-based Routing Framework that enables distributed and privacy-preserving model training across multiple network domains. By exchanging only model parameters instead of raw telemetry data, the system enhances privacy, reduces communication overhead, and maintains strong routing performance. Simulation results show improved delay, throughput, and packet delivery ratio compared to centralized ML routing. The proposed approach is scalable and suitable for real-world deployment in multi-domain SDN and 5G environments.

Future work will explore integration of Graph Neural Networks or Graph Transformers to capture topological relationships within federated setups. Asynchronous FL will be implemented to accommodate variable update rates across routers. Federated reinforcement learning (FRL) will be investigated to enable policy learning for dynamic routing decisions. Real-world deployment using ONOS or Ryu SDN controllers will validate performance under realistic traffic conditions. Additionally, extending to federated multi-agent systems can facilitate collaborative optimization across inter-domain networks.

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