International Journal of Innovation Studies

INTELLIGENT TRAFFIC ENGINEERING IN SOFTWARE-DEFINED NETWORKS USING FEDERATED DEEP REINFORCEMENT LEARNING

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ABSTRACT: In this context, Software-Defined Networking (SDN) has been recognized as a key enabling platform for future programmable networks. Nevertheless, traditional traffic engineering techniques often struggle to meet the requirements of large-scale, multi-domain environments while ensuring the privacy of network traffic. In this paper, we propose a novel framework for intelligent traffic engineering using Federated Deep Reinforcement Learning (FDRL). In this context, the key novelty of this paper is that the proposed technique allows distributed SDN controllers to collaborate and learn the optimal routing strategies without the need to exchange raw network traffic information. This is achieved by integrating federated learning and deep reinforcement learning techniques. Simulation results demonstrate that the proposed FDRL framework significantly improves network performance compared with traditional shortest-path routing and centralized DRL methods, achieving higher throughput, lower latency, and reduced packet loss. These results indicate that federated deep reinforcement learning provides an effective solution for intelligent traffic engineering in next-generation SDN environments.

Keywords: Software-Defined Networking, Traffic Engineering, Federated Learning, Deep Reinforcement Learning, Intelligent Network Optimization, Multi-Domain SDN.

1. INTRODUCTION

The exponential growth in the usage of cloud services, real-time multimedia applications, and IoT devices has led to increased complexity in managing computer network traffic. Software-

Defined Networking (SDN) has emerged as a solution to this problem by separating the control plane from the data plane. Despite the advantages offered by SDN in network management, centralized SDN faces scalability issues, increased latency in control signals, and privacy issues in large-scale networks. Recent developments in Deep Reinforcement Learning (DRL) have demonstrated its potential in providing intelligent network management using machine learning to learn optimal network routes. However, centralized DRL requires significant data exchange among network entities, making it impractical in multi-domain networks. To overcome these issues in centralized DRL, this research proposes a Federated Deep Reinforcement Learning (FDRL) framework for intelligent traffic management in SDNs.

2. LITERATURE REVIEW

With the advent of Software-Defined Networking (SDN), the architecture of the network has been transformed with the decoupling of the control plane and the data plane. Nick McKeown et al. introduced the concept of OpenFlow in the article "[1] OpenFlow: Enabling Innovation in Campus Networks." This concept was the foundation for the invention of SDN, which allowed the innovation of campus networks. Thomas D. Nadeau and Ken Gray presented a comprehensive overview of the architecture of SDN in the article "[2] SDN Architecture." The article focused on the flexibility and programmability of SDN architecture and its ability to dynamically manage the flow of traffic. Mao et al. presented a comprehensive survey on the concept of SDN-traffic engineering (TE) in the article "[3] Traffic Engineering in Software-Defined Networking."
With the development of artificial intelligence, ML techniques are being employed in SDN-based systems to facilitate efficient traffic management. In this context, Mao et al. [4] suggested a learning-based networking technique, which proved the effectiveness of DRL in controlling the network. Among all DRL techniques, PPO, which is a reinforcement learning technique introduced by John Schulman et al. [5], is used to update policies efficiently and stably, making it more efficient in a dynamic and complex networking environment.

In recent years, researchers have used DRL techniques to develop efficient and effective SDN-based TE systems. In this context, Liu et al. [6] introduced a DRL-based TE technique, which proved that DRL-based TE is more efficient and effective in terms of throughput and congestion. In another study, Xu et al. [14] introduced an experience-driven networking technique, which uses DRL to develop efficient routing techniques. In another study, Elgamal et al. [15] proved the effectiveness of DRL-based TE in an SDN-based environment. In a multi-domain and distributed environment, Wang et al. [11] introduced a reinforcement learning-based TE technique.
Another field where multi-agent reinforcement learning (MARL) is gaining popularity is distributed network optimization. Zhang et al. presented a comprehensive overview of the applications of MARL techniques, focusing on the significance of the approach in decentralized decision-making processes such as multi-controller SDN architecture.

Regarding the issues of privacy and communication in the context of distributed learning processes, federated learning (FL) is considered a promising approach. Konečný et al. presented strategies for the improvement of the communication efficiency of FL systems, while Yang et al. presented the concept and applications of federated machine learning. Wang et al. presented the application of FL mechanisms in the context of resource-constrained edge environments.

Deep learning applications have been extensively explored in the context of wireless and mobile networks. Zhang et al. presented a comprehensive overview of the applications of deep learning techniques in the context of mobile and wireless networks, focusing on the significance of the approach in the context of traffic prediction and resource allocation. Chen et al. presented the application of the learning approach using artificial neural networks in the context of wireless systems.

3. SYSTEM ARCHITECTURE AND PROBLEM FORMULATION

3.1 Network Architecture

The proposed system consists of multiple SDN domains, each managed by a local controller. Each controller hosts a DRL agent responsible for local routing decisions. A federated aggregation server coordinates model updates without accessing raw traffic data.

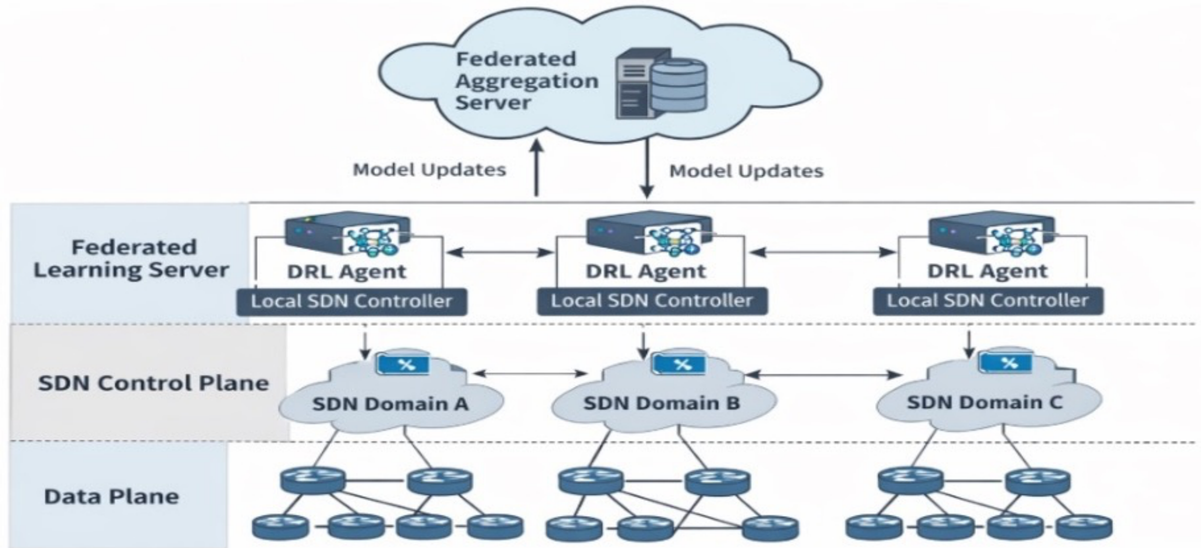

Figure 1: Proposed Federated DRL-based SDN Architecture.

Figure 1 presents the proposed Federated Deep Reinforcement Learning (FDRL) framework for intelligent traffic engineering in Software-Defined Networks. In this proposed architecture, multiple Software-Defined Networks (SDNs) are controlled by local controllers, where each controller is equipped with a Deep Reinforcement Learning (DRL) agent that learns the optimal routing decisions based on local network states such as link utilization, delay, and queue length. Instead of exchanging raw data related to the network traffic, each controller sends the encrypted model parameters at periodic intervals to the federated aggregation server. The federated aggregation server aggregates the model parameters from the local controllers and sends the aggregated model parameters to all the controllers.

3.2 Problem Formulation

The traffic engineering problem is modeled as a Markov Decision Process (MDP):
State s: link utilization, queue length, and end-to-end delay
Action at: selection of routing paths or traffic splitting ratios

Reward rt: reflects network performance.

Objective Function

The traffic engineering problem is formulated as maximizing cumulative discounted reward:

$$\max_{\pi} E\left[\sum_{t=0}^{T} \gamma^{t} rt\right] \qquad \text{Eq. (1)}$$

Where:

π= routing policy

γ∈(0,1)= discount factor

rt = reward at the time stamp t.

The objective function is stated in (1) as a reinforcement learning (RL) method of maximizing expected discounted rewards received from some policy π.

Reward Function

$$\mathrm{rt} = \alpha \cdot \mathrm{Throughputt} - \beta \cdot \mathrm{Delayt} - \delta \cdot \mathrm{PacketLosst} \qquad \text{Eq. (2)}$$

Where:

α,β,δ are weighting factors.

Equation (2) describes how to calculate a reward function based on the throughput, delay and packet loss of the network as a weighted optimization metric.

Traffic engineering is modeled as a Markov Decision Process (MDP):

Component	Description
State	Link utilization, queue length, latency
Action	Path selection and traffic splitting
Reward	Weighted function of throughput, delay, and packet loss

The objective is to maximize cumulative reward by learning optimal routing policies.

4. PROPOSED FEDERATED DEEP REINFORCEMENT LEARNING FRAMEWORK

4.1 Local DRL Agent

To carry out adaptive traffic engineering in real-time, each SDN controller contains a local DRL agent that can leverage all current information available from the observed state of the network. The routing problem is formulated as Markov decision process, the agent making optimal path allocation decisions that will maximize network performance over time. To approximate the action-value function and improve routing policies iteratively, a DQN (Deep Q-network) will be used to perform the learning process using reward feedback based on three components of network performance: throughput, latency, and packet loss. The training of the agent will occur locally in each SDN domain to maintain the privacy of data while allowing for intelligent routing optimization, which is based on congestion management and knowledge of how best to use the network.

4.2 Federated Learning Process

After the local training iterations have been completed, local controllers send model parameters encrypted to the federated aggregation server on a regular basis. The server constructs and aggregates weighted averaged updates of the local parameters from the local training controllers to produce an improved global model; through this process, the server aggregates model knowledge from several different SDN domains into one global model version. The global model parameters are then sent to all active participating controllers to facilitate the synchronous collaborative learning process. This repetitive cycle produces cooperative intelligence and increases both the scalability of the federated methodology and data privacy since there is no exchange of traditional data, i.e., raw data of traffic.

Q-Learning – DQN Update rule

$\mathrm{Q(st, at) \leftarrow Q(st, at) + \eta(rt + \gamma a'maxQ(st + 1, a') - Q(st, at))}$ Eq. (3)

Where:

η = learning ratex

γ = discount factor

The DQN update rule for continuing to improve routing decisions is described in Equation (3).

Federated Learning Aggregation Equation

The Equation (4) describes the federated averaging algorithm where local SDN controllers will update global model parameters collaboratively while not sharing any raw traffic data to ensure they can scale properly and keep end-user traffic private.

$\theta^{(t+1)} = \sum_{i=1}^{N} \frac{ni}{n} \theta i^{t}$ Eq. (4)

- θi = local model parameters
- ni = local dataset size
- n=∑ni
- N= number of SDN domains

This represents Federated Averaging (FedAvg).

Algorithm: Federated DRL-Based Traffic Engineering

Initialize global DRL model θ
Distribute θ to all SDN controllers
for each federated round do
  for each SDN controller i in parallel do
    Observe network state si
    Select action ai using policy πθ
    Execute routing decision
    Receive reward ri
    Update local model θi
  end for
  Aggregate local models:
    θ ← Σ wi θi
 Broadcast updated θ to all controllers

end for

The proposed federated deep reinforcement learning (FDRL) based software-defined networking (SDN) architecture. Multiple SDN domains with their own local DRL agents conduct independent traffic engineering operations and exchange encrypted model updates with a federated learning server. The global model is iteratively aggregated and distributed for cooperative intelligence.

5. PERFORMANCE EVALUATION

5.1 Simulation Setup

Table 1: Simulation parameters

Parameter	Value
Network Type	Multi-domain SDN
Traffic Pattern	Dynamic Poisson flows
Learning Model	DQN with Federated Aggregation
Baselines	Shortest Path, Centralized DRL

5.2 Results and Analysis

Table 2. Performance Comparison

Method	Throughput (%)	Latency (ms)	Packet Loss (%)
Shortest Path	65	120	4.8
Centralized DRL	82	85	2.6
Proposed FDRL	92	60	1.3

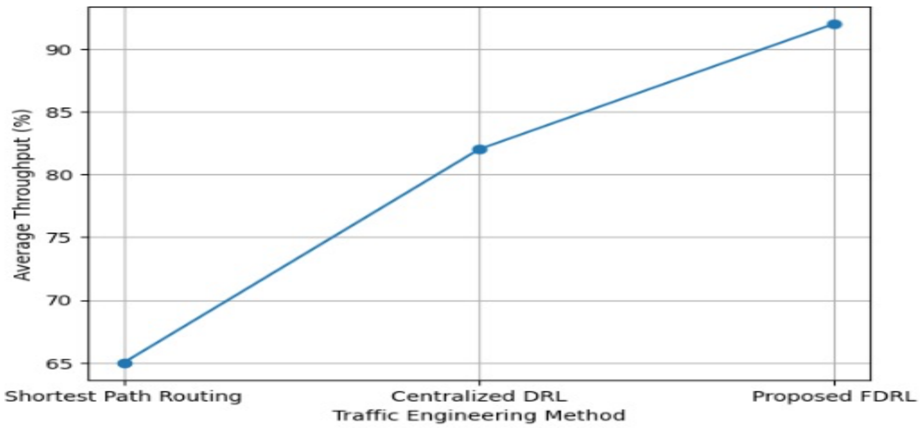

Figure 2. Throughput comparison of traffic engineering approaches.

Figure 2 shows the average network throughput of three traffic engineering techniques: the traditional shortest path routing, centralized deep reinforcement learning, and the proposed federated deep reinforcement learning. The results show the effectiveness of the proposed FDRL model in outperforming other techniques under dynamic traffic conditions.

Compared to the shortest path routing technique, the FDRL technique achieves a much better network throughput by using dynamic routing techniques according to the real-time network states. In comparison with the centralized deep reinforcement learning technique, the proposed FDRL technique achieves better network performance through collaboration with other SDN domains. Therefore, the effectiveness of the proposed FDRL model in achieving better network performance through the federated intelligence concept makes it suitable for large-scale and multi-domain Software-Defined Networks.

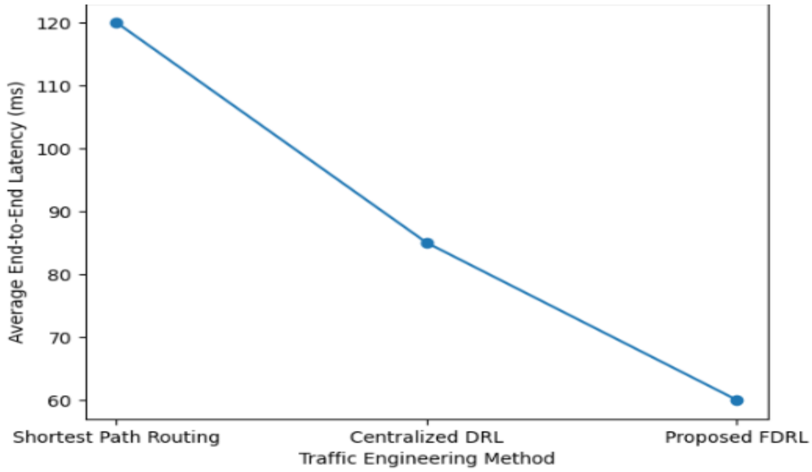

Figure 3. End-to-end latency comparison of traffic engineering approaches.

Figure 3 shows a comparison of the average end-to-end latency that is obtained using different traffic engineering techniques. As shown in the figure, the proposed FDRL technique minimizes latency by making routing decisions based on real-time network conditions. In comparison to the shortest path routing technique, latency is reduced by almost half, which proves the effectiveness of the technique.

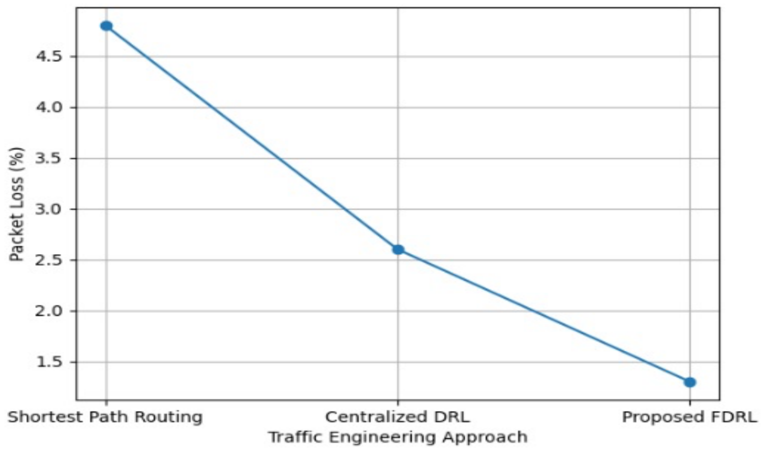

Figure 4. Packet Loss Comparison of Traffic Engineering Approaches

The proposed federated deep reinforcement learning (FDRL) technique is observed to have the lowest packet loss ratio when compared to the shortest path routing and centralized DRL. This is due to the dynamic adaptation of the routing strategies and the collaborative learning of the congestion-aware strategies.

6. DISCUSSION

The results have also validated that the federative learning approach improves scalability and privacy while maintaining high performance. Unlike the centralized DRL model, the suggested model minimizes communication costs and data sharing. From the results obtained in this study, it is evident that the integration of federative learning with deep reinforcement learning improves traffic engineering in SDNs significantly. Unlike centralized DRL models, the suggested model minimizes data sharing and communication costs. These results have validated that the federative deep reinforcement learning model is a viable solution for intelligent traffic engineering in large-scale and multi-domain SDN environments. These results have also validated that the suggested model has a high potential to be used in real-world environments where data privacy and scalability are major concerns.

7. CONCLUSION AND FUTURE WORK

This paper proposed an intelligent traffic engineering framework for Software-Defined Networks using the concept of federated deep reinforcement learning. In this context, the paper demonstrated how the incorporation of federated learning with distributed SDN controllers facilitates effective and adaptive traffic optimization without the need to exchange raw traffic information. This way, the proposed framework overcomes the limitations of scalability and privacy, which are inherent in centralized deep reinforcement learning-based traffic engineering frameworks. In this context, the paper showed through comprehensive simulation results how the proposed FDRL-based framework outperforms other conventional techniques, like traditional shortest-path routing and centralized DRL-based traffic optimization, in terms of various performance parameters. For instance, the proposed framework ensures better network throughput, reduced end-to-end delay, and packet loss, with faster and more stable learning convergence.

The results of this study suggest that federated deep reinforcement learning is a promising solution for intelligent traffic engineering in large-scale and multi-domain SDN environments. In this context, the proposed framework is expected to play a key role in providing a viable solution for future intelligent networking systems. In this direction, future works are expected to investigate the applicability of the proposed solution in real-world SDN testbeds, as well as the extension of the framework to multi-agent coordination scenarios and other emerging network infrastructures, such as edge computing and 6G networks.

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