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Comparative Performance Analysis Of Drl Algorithms For Intelligent Traffic Engineering In Sdn

[1] Dr. Shweta Singh, [2]Dr. Kalpana Rai, [3] Dr. Vandana Rai, [4]Prof. Aakrati Verma, [5] Dr. Nidhi Singh
[1]Associate Professor, [2] Professor, [3] Assistant Professor, [4] Assistant Professor [5] Associate Professor
[1]Department of Artificial intelligence and Machine Learning,
[1]Sagar Institute of Research and Technology, Bhopal, India

Abstract: As the network requirements are increasing due to the increased traffic load given by 5G networks, the traditional methods for network management are not efficient to handle this traffic. Traditional traffic engineering (TE) solutions which uses static routing protocols and heuristic based load balancing can not handle highly dynamic and bursty nature of modern traffic which leads to inefficient resource utilization and compromised QOS. Software-Defined Networking (SDN) IS a transformative architectural paradigm by connecting the control plane with the data plane and hence facilitating programmable and agile traffic management. Deep Reinforcement Learning (DRL) offers a potent, model-free approach to intelligent TE, enabling agents to learn optimal routing policies through continuous interaction with the network environment. This paper provides the comparison of various DRL algorithms used for SDN-TE, Deep Q-Networks (DQN), Asynchronous Advantage Actor-Critic (A3C) and Proximal Policy Optimization (PPO) are compared on the basis of latency and throughput.. Experimental results demonstrate that DRL-based agents can achieve up to a 30% reduction in latency and a 60% improvement in throughput compared to traditional routing baselines. The study also addresses critical implementation challenges, including scalability and the integration of Graph Neural Networks (GNNs) for enhanced generalization.

Index Terms: *software defined network, deep reinforcement learning, deep Q network, routing*

I. Introduction

The modern networking landscape is undergoing a fundamental transformation driven by the massive growth of Internet of Things (IoT) applications. Projections indicate that the rapid deployment of smart IoT devices will reach approximately 22.3 billion by 2024, generating a staggering 163 zettabytes of data by 2025.[1] This tidal wave of information places an unprecedented burden on existing network infrastructures, which were originally designed over four decades ago for a relatively static environment.[2] Traditional networking architectures, where the control and data forwarding planes are tightly coupled within individual devices, are notoriously difficult to configure and manage.[1] This coupling limits the network's ability to respond to transient traffic spikes and dynamic topology changes, often resulting in network congestion and compromised performance.[4]

Software-Defined Networking (SDN) represents a paradigmatic shift that addresses these limitations by centralizing the network's control logic in a logically centralized controller.[1] This separation empowers network operators to monitor and manage traffic with unprecedented agility and flexibility.[1] The SDN controller, acting as the "brain" of the network, collects real-time data from forwarding switches and dynamically configures flow tables.[6] While SDN provides the necessary framework, the implementation of adaptive Traffic Engineering (TE) remains a complex challenge. Traditional TE methods often rely on centralized linear programming or heuristic updates to link weights, which may be computationally prohibitive for large-scale networks or fail to capture the non-linear dynamics of real-world traffic.[8]

II. Literature Review

The integration of intelligent algorithms into SDN has been a focal point of recent networking research.[3] Early efforts by Valadarsky et al. [9] demonstrated that reinforcement learning could adapt to changing network conditions, although their initial approach did not leverage deep learning architectures. Stampa et al. [10] were among the first to specifically apply Deep Q-Networks (DQN) to SDN routing, showing significant improvements over traditional Dijkstra-based methods. This was further expanded by Xu et al. [11], who proposed "DRL-TE," a model-free control framework that utilizes Actor-Critic networks and prioritized experience replay to optimize traffic split ratios in real-time.[11]

Research has also addressed the negative impacts of frequent flow rerouting, such as packet out-of-order delivery. Zhang et al. [12] introduced "CFR-RL" (Critical Flow Rerouting), a scheme that identifies a small subset of "critical flows" for rerouting, thereby minimizing network disturbance while achieving near-optimal link utilization.[12] To overcome the scalability issues inherent in large-scale topologies, Rusek et al. [13] proposed "RouteNet," a novel model based on Graph Neural Networks (GNNs) capable of predicting performance metrics like delay and jitter across arbitrary network structures.[13]

For next-generation infrastructures, recent studies have explored Multi-Agent DRL (MADRL). Kołakowski et al. [2] detailed the exploitation of DRL for 6G-enabled mobile network planes, while the 3DQR framework [14] utilizes MADRL and GNNs to coordinate traffic across integrated terrestrial and satellite segments.[14] Furthermore, comparative studies by Abbasova and Karimova [5] have established that Proximal Policy Optimization (PPO) offers superior stability and faster convergence compared to DQN and A3C in dynamic SDN-TE environments.[5]

III. Evolution of Traffic Engineering Paradigms

To appreciate the significance of DRL in SDN, one must examine the limitations of historical TE approaches. Traditional protocols like Open Shortest Path First (OSPF) compute paths based on static link costs, which frequently leads to the creation of "hotspots" where certain links are over-saturated while others remain underutilized.[5] Equal-Cost Multi-Path (ECMP) was introduced to mitigate this by splitting traffic evenly among multiple paths, yet it often uses hash-based splitting that is insensitive to flow sizes.[12]

The integration of Reinforcement Learning (RL) into the SDN control plane represents the third wave of TE evolution. Early research into tabular RL demonstrated that agents could learn to minimize latency by iteratively updating Q-tables, but these methods suffer from the "curse of dimensionality" as network size grows.[6] Deep Reinforcement Learning (DRL) overcomes this by using deep neural networks (DNNs) to approximate value functions or policies, enabling the management of large-scale topologies and continuous action spaces.[1]

IV. Theoretical Framework of DRL in Networks

The application of DRL to Traffic Engineering requires formulating the routing problem as a Markov Decision Process (MDP). In this setup, the DRL agent, typically residing in the SDN controller, interacts with the network environment over discrete decision epochs t.[11]

A. The MDP Components for Networking

A network MDP is defined by the 5-tuple (S, A, R, p, y) [11]:

1. State Space (S): The state S_t represents the agent's observation of the network, including link utilization matrices, traffic demand per source-destination pair, and queue lengths.[5] Advanced models incorporate graph-structured information to capture topological relationships.[13]
2. Action Space (A): The action a_t is the decision made by the agent. This can be discrete, such as choosing paths among k candidates, or continuous, such as determining specific split ratios w_{kj} for traffic across multiple pathways.[11]
3. Reward Function (R): The reward r_t is the signal that guides learning, derived from KPIs such as

throughput, latency, and packet loss.[5] The objective is to maximize the discounted cumulative reward .[11]

V. Core DRL Algorithms for SDN-TE

A. Deep Q-Networks (DQN)

DQN is a value-based method that uses a DNN to approximate the Q(s,a) function.[5] While conceptually simple, DQN can struggle with high-dimensional action spaces in dynamic tasks.

B. Asynchronous Advantage Actor-Critic (A3C)

A3C utilizes a parallelized architecture where multiple worker agents explore different instances of the network environment simultaneously.[5] Studies indicate that A3C can achieve approximately a 9-10% reduction in latency and a 7% gain in throughput over traditional ECMP baselines.

C. Proximal Policy Optimization (PPO)

PPO has emerged as a preferred algorithm due to its stability and sample efficiency.[5] It uses a clipped surrogate objective function to prevent large, destabilizing policy updates. Evaluations on 10-node networks showed that PPO reduced average flow latency by ≈20% and packet loss by ≈25% relative to shortest-path routing.

VI. Advanced Frameworks and System Architectures

A. CFR-RL: Critical Flow Rerouting

Frequent rerouting can lead to packet reordering and network disturbance.[12] CFR-RL addresses this by identifying a small subset of "critical flows" (typically elephant flows) that contribute most to congestion.[12] The DRL agent selects these flows, and a Linear Programming (LP) module recomputes their paths.[12] Extensive evaluations show that CFR-RL achieves near-optimal performance by rerouting only 10% to 21.3% of total traffic.[12]

B. 3DQR and MADRL for 6G Networks

Future 6G infrastructures will integrate terrestrial and non-terrestrial (Satellite) segments.[2] The 3DQR (3D QoS-aware Routing) framework utilizes Multi-Agent DRL (MADRL) and Graph Neural Networks (GNNs) to coordinate traffic across these diverse domains.[14]

VII. Experimental Results and Analysis

Experimental evaluations across topologies like NSFNET (14 nodes) and GÉANT (24 nodes) highlight significant improvements.[12]

- Latency: PPO-based agents reduced average flow latency by ≈20-30% compared to shortest-path routing.
- Throughput: Aggregate throughput under PPO can be as much as 60% higher than shortest-path methods.
- Packet Loss: PPO reduced packet loss by approximately 40% in relative terms compared to standard Dijkstra baselines.

Table 1: Comparison of PPO, A3C and DQN

Metric	PPO Improvement	A3C Improvement	DQN Improvement
Latency	~20-30%	~10%	~5-7%
Throughput	~60%	~7%	~15%
Packet Loss	~25-40%	~10-15%	~5%

VIII. Implementation Challenges

As the number of nodes increases, the traffic matrix grows quadratically, making centralized processing difficult.[5] Furthermore, training in discrete-event simulators like ns-3 can be slow, sometimes taking over 3 days for 100 epochs.[8]

IX. Future Work

The transition of DRL-based Traffic Engineering from research to carrier-grade deployment requires addressing several emerging frontiers.

1. Transfer and Continual Learning: Research into Transfer Learning is essential for accelerating DRL deployment across heterogeneous topologies by reusing knowledge from previously trained environments.[15] Furthermore, Online Continual Learning methods are required to allow controllers to adapt to evolving traffic patterns without the overhead of retraining from scratch.[15]
2. Multi-Agent Coordination (MARL): Future architectures should exploit Multi-Agent Reinforcement Learning (MARL) to facilitate the coordination of multiple autonomous controllers managing distinct network segments or flow classes, ensuring global optimization without centralizing all processing.[15]
3. Differentiable Network Modeling: To address the training bottleneck of discrete-event simulators, future work should investigate fully-differentiable network models like dNE, which enable faster gradient-based optimization and drastically reduce simulation time during the learning phase.[8]
4. Reward Function Optimization: Refining multi-objective reward functions that capture a broader state representation, including energy efficiency and security metrics, remains a priority.[5] Focusing specifically on high-rate flows for direct routing can also enhance system scalability.[21]

X. Conclusion

The integration of Deep Reinforcement Learning into SDN has fundamentally transformed Traffic Engineering. By leveraging centralized visibility and adaptive learning, DRL agents effectively minimize latency and maximize throughput compared to static protocols. While challenges in scalability and training time remain, the emergence of transfer learning, multi-agent coordination, and differentiable simulators provide a clear path toward carrier-grade implementation for future 6G networks.

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