Enhancing Traffic Engineering with AI: Comparative Analysis of Mpls, Sd-WaN, and SRv6

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ABSTRACT

Modern networks must manage dynamic traffic driven by 5G, IoT, and cloud services. Traditional traffic engineering (TE) technologies such as static routing cannot react in real time, leading to congestion and degraded performance. Predictive and adaptive capabilities come through artificial in- telligence (AI) to overcome these shortcomings.

This article compares three classic TE technologies: Segment Routing over IPv6 (SRv6), SoftwareDefined Wide Area Network- ing (SD-WAN), and Multiprotocol Label Switching (MPLS). Each has unique trade-offs: MPLS provides deterministic QoS at a high cost and limited flexibility; SD-WAN provides cost-effective flexibility but does not provide guaranteed QoS; SRv6 makes source routing programmable at the cost of header overhead and scalability demands. To address these drawbacks, we present a TE framework based on AI that leverages predictive analytics for predicting flows and RL to provide adaptive path selection choices. The model was evaluated with simulated enterprise-scale topologies supporting composite traffic mixtures of voice, video, and data. Outcomes demonstrate that AI-driven TE significantly reduces latency and packet loss while improving throughput and cost savings over static TE controls. Predictive rerouting, in particular, achieved double-digit latency savings, while RL dynamically distributed load between MPLS, SD-WAN, and SRv6 paths.

These findings confirm that AI-based TE enhances perfor- mance, scalability, and flexibility and is a suitable solution for future heterogeneous and high-traffic networks.

INTRODUCTION

The rapid expansion of cloud computing, Internet of Things (IoT) installations, mobile broadband, and latency-critical ap- plications such as augmented reality (AR) and real-time an- alytics has transformed the requirements of future-generation communication networks drastically. These applications gen- erate extremely dynamic and heterogeneous traffic patterns that are putting pressure on traditional Traffic Engineering (TE) mechanisms. While traditional practices—often involv- ing static allocation and humanbased configuration interven- tion—have been sufficient for the predictably stable workloads of the past, they do not suffice in the face of today's network environments' burstiness, variability, and stringent Quality of Service (QoS) demands.

Traffic Engineering is necessary for the optimization of network resource utilization, ensuring service-level agreements (SLAs), and cost-effectiveness. Conventional TE solutions have conventionally relied on deterministic algorithms and centralized planning for load balancing, congestion prevention, and traffic prioritization. These static or semi-static strategies are, nonetheless, diminishing in effectiveness in environments in which traffic matrices are refreshed at sub-second time scales and where service agility is predominant.

Multi-Protocol Label Switching (MPLS) provides a proven backbone technology for TE in large-scale Internet Service Provider (ISP) networks and enterprise infrastructure over several years. The deterministic performance guarantee of MPLS provides an effective match for mission-critical appli- cations. MPLS

provisioning, nonetheless, can be costly and cumbersome, and having LSPs dynamically adapt to rapidly changing traffic involves large operational overhead.

SD-WAN subsequently emerged as a more flexible answer, based on application-aware routing and numerous supporting transport technologies like broadband Internet and LTE/5G links. While SD-WAN is cost-effective and can be deployed quickly, it is not able to provide QoS natively because it is based on best-effort Internet paths. Additionally, in the majority of commercial SD-WAN offerings, control-plane intelligence remains confined to pre-defined policies, with no predictive responsiveness.

Segment Routing over IPv6 (SRv6) is a more recent model that simplifies network programming by inserting instructions into the IPv6 header. SRv6 is more flexible and more scalable than MPLS in certain use cases, offering source-based routing without per-flow state at the intermediate nodes. SRv6's larger headers increase processing overhead and lower efficiency on certain hardware platforms, particularly where there is high throughput and low latency.

The use of Artificial Intelligence (AI) in TE offers a possible solution to these constraints. Machine learning (ML) models can forecast traffic demand, identify patterns, and detect anomalies, enabling proactive rather than reactive network readjustment. Reinforcement Learning (RL), in particular, en- ables continuous adaptation to network development, learning routing policies by trial and error through interaction with the environment. Through the assistance of Software-Defined Networking (SDN) controllers, AI-driven TE can offer both agility and deterministic performance.

This paper presents an AI-empowered TE framework that integrates predictive analytics and RL to adaptively optimize WAN routing in heterogeneous topologies. We compare its performance on MPLS,
SD-WAN, and SRv6 configuration under a controlled emulation environment using the same topologies and traffic patterns. The research presents compar- ative evaluation with trade-offs in latency, throughput, cost-effectiveness, and scalability.

The rest of the paper is organized as follows: Section II reviews previous research in AI-driven TE and the three tech- nologies under consideration. Section **??** presents the AI-TE framework and simulation environment developed. Section IX is devoted to experimental results, while Section **??** discusses trade-offs and implications. Section **??** summarizes the paper and outlines future work directions.

Related Work (2020–2025)

Recent years have seen an accelerated convergence of arti- ficial intelligence (AI) techniques and traffic engineering (TE) research. Several survey and application papers have explored the use of machine learning (ML) and deep reinforcement learning (DRL) for traffic prediction, anomaly detection, and dynamic network routing optimization. For example, Kablaoui *et al.* propose novel time-series-to-image transformations for improved network traffic prediction, demonstrating that deep models can effectively forecast short-term demand patterns relevant to TE decisions [12]. Zheng *et al.* experimentally evaluate flow-level traffic-matrix prediction approaches and show their potential to inform fine-grained resource alloca- tion in WANs [14]. Complementing forecasting work, Yang presents hybrid statistical–neural forecasting (SA-ARIMA-BP) showing robust short-term prediction for bursty traffic [15].

DRL has been widely applied to dynamic routing and load balancing. Troia *et al.* investigate DRL for SDWAN traffic engineering, showing that learning-based controllers can meet QoS targets under variable loads [10]. Pei *et al.* and Botta *et al.* extend RL approaches to SDN/SD-WAN contexts, demonstrat- ing that singleagent and multi-agent learning can adaptively select overlay paths and improve end-to-end performance [2], [3]. Lu *et al.* propose graph-based RL approaches (GNN+RL) for scalable TE in SDN, indicating strong generalization across topologies [11]. Alenazi explores deep Q-learning for QoS improvements in the physical layer of SDN systems, reinforcing the value of RL across protocol layers [13].

Work specifically targeting classical TE technologies com- plements these AI efforts. Masood *et al.* introduce

evolu- tionary optimization techniques for MPLS networks, showing improvements in link utilization and delay under realistic constraints [4]. Grgurevic *et al.* present an experimental com- parison between MPLS and SD-WAN using GNS3 emulation, highlighting SD-WAN's cost and flexibility advantages in enterprise settings [7]. Borgianni *et al.* investigate migration strategies from MPLS to SD-WAN to maintain cloud QoS, providing practical insights into hybrid deployments [8].

Segment Routing (SR), in particular SRv6, has been studied as a next-generation TE mechanism. Wu and Cui provide a comprehensive survey of SR-based TE capability and compare SRv6's source-routing paradigm with MPLS-TE [5]. Tian *et al.* explore DRL techniques for SRv6 deployments in partially-upgraded networks, illustrating DRL's effectiveness for segment-list optimization when full SRv6 support is not ubiquitous [1]. Scarpitta *et al.* and other SRv6 authors demon- strate practical SRv6 monitoring and in-kernel implementations (e.g., eBPF) that minimize forwarding overhead while providing fine-grained telemetry for TE [24].

Recent surveys synthesize these threads, emphasizing hy- brid and AI-driven TE frameworks for future networks. Ouamri *et al.* survey SD-WAN principles and challenges and identify TE and AI automation as priority research directions [6]. Aktas *et al.* and Wang *et al.* outline broader visions for AI-enabled routing and mixed-integer optimization in hybrid SDN/MPLS/SRv6 environments [16], [17]. Work on cost- aware and scalable TE, including cloud- and edge-enabled AI controllers, suggests that AI can enable incremental migration paths (e.g., SD-WAN overlays on SRv6-enabled cores) while preserving operator SLAs [18], [19].

Briefly, the literature (2020–2025) indicates (1) great progress in traffic forecast and flow forecast techniques to be used in TE, (2) efficient use of DRL in adaptive routing and overlay management, and (3) growing interest in SRv6 and hybrid approaches as substitutions or complements for MPLS and SD-WAN. Our research builds on these studies using a unified AI-enabled TE approach and the direct comparison between MPLS, SD-WAN, and SRv6 under the same emulation test cases to derive actionable recommendations for operators considering AI-assisted migration or hybrid deployment.

EXTENDED LITERATURE REVIEW (2020–2025)

This extended review examines recent advancements in AI- enhanced traffic engineering across the three core technolo- gies—MPLS, SD-WAN, and SRv6—and highlights insights relevant to our contributions.

A. AI and Optimization in MPLS

1. Masood *et al.* (2025) introduce an evolutionary Bat algorithm for MPLS traffic optimization, enhancing link utilization and reducing packet delay under realistic con- straints [4].
2. Grgurevic *et al.* (2021) provide empirical comparison between MPLS and SD-WAN via GNS3, emphasizing MPLS's QoS guarantees but noting its lower flexibility and higher cost [7].
3. Borgianni *et al.* (2023) examine migration strategies from MPLS to SD-WAN to sustain cloud application QoS, discussing both performance trajectories and practical deployment trade-offs [8].

B. AI-Driven Techniques in SD-WAN

1. Troia *et al.* (2021) apply deep reinforcement learning for traffic engineering in SD-WAN, achieving dynamically adaptive routing that meets QoS under variable loads [10].

2. Pei *et al.* (2024) extend RL to SDN environments, op- timizing routing for heterogeneous traffic with improved delay-throughput trade-offs [3].

3. Botta *et al.* (2024) propose a multi-agent RL framework at SD-WAN edges that adapts overlay path selection in real time, enhancing resilience and throughput [2].

4. Alam *et al.* (2025) outline a comprehensive AI/ML- based framework for traffic engineering suited to dynamic enterprise networks, relevant for SD-WAN orchestration [9].

C. Segment Routing (SRv6) and AI

1. Tian et al. (2020) explore DRL for TE in partially deployed SRv6 networks, showing that AI can optimize segment lists even when full SRv6 support is not available [1].

2. Scarpitta et al. (2023) implement high-performance de- lay monitoring using eBPF in SRv6-based SDWANs, demonstrating minimal forwarding overhead—key for AI-enabled, real-time telemetry [24].

3. Wu and Cui (2023) provide a comprehensive survey com- paring SRv6-based TE with MPLS-TE; they highlight SRv6's state-less scalability and flexibility for source routing, essential for AI-driven control [5].

4. D. Cross-Technology AI Future-Oriented Frameworks

5. Ouamri et al. (2025) survey SD-WAN technologies, em- phasizing future research in AI-automated TE and multi- domain orchestration [6].

6. Aktas et al. (2025) review AI-enabled routing in next- generation networks, advocating for hybrid TE that merges MPLS, SD-WAN, and SRv6 under AI control [16].

7. Wang et al. (2025) propose mixed-integer nonlinear programming and heuristic algorithms for TE in hy- brid SDN/MPLS environments, highlighting scalable op- timization under complex constraints [17].

8. Gupta and Kumar (2023) analyze traffic optimization using AI and segment routing techniques in SDWAN, bridging SRv6's programmability with overlay flexibility [19].

Summary: The existing literature indicates that AI, es- pecially DRL and predictive analytics, has been effectively applied in MPLS, SD-WAN, and SRv6 individually to im- prove the routing agility, performance, and resiliency. Not many studies offer direct comparative evaluation of all three technologies under the same test setup. This study fills this gap by comparing AI-enhanced TE consistently across MPLS, SD-WAN, and SRv6 under controlled simulation.

Technology Overview

This chapter provides a concise technical overview of the three principal traffic engineering (TE) technologies be- ing compared in this study: Multi-Protocol Label Switch- ing (MPLS), Software-Defined Wide Area Networking (SD- WAN), and Segment Routing over IPv6 (SRv6). Their design principles, operation models, and trade-offs need to be under- stood in order to set into context the comparative analysis and simulation results that follow.

A. Multi-Protocol Label Switching (MPLS)

MPLS is a high-performance forwarding technology that transports packets based on short, fixed-length labels rather than IP addresses. Pre-established Label-Switched Paths (LSPs) are established using signaling protocols such as RSVP-TE or LDP to enable predictable Quality of Service (QoS) and effective traffic engineering. By decoupling the for- warding plane from network-layer addressing, MPLS has the ability to provide head-of-line-blocking priority for latency- sensitive traffic, reserve bandwidth, and recover traffic in a matter of seconds during failures. Yet, its use of pre- provisioned circuits raises operational expense and lowers flexibility in environments of dynamic traffic. Additionally, MPLS deployment often entails specialized hardware and a homogeneous core infrastructure.

1. **Software-Defined Wide Area Networking (SD-WAN):** SD-WAN overlays the WAN with encrypted transport- independent tunnels over various transports like broadband Internet, LTE/5G, and MPLS.

Centralized controllers utilize real-time performance metrics (e.g., latency, jitter, packet loss) to dynamically select the best path for each application. SD- WAN reduces costs by leveraging lower-cost Internet links and offers distributed enterprises rapid scalability. Its limitations are that it does not have built-in QoS guarantees over public networks and can be subject to the monitoring of overlay and encryption overhead performance. SD-WAN is appropriate for fast deployments and hybrid cloud integration but can be sensitive to congestion within the underlay network.

2. **Segment Routing over IPv6 (SRv6):** SRv6 implements source routing by encapsulating a sequence of ordered instruc- tions, or segments, into the IPv6 header as the Segment Rout- ing Header (SRH). This eliminates label distribution protocol requirements and allows for flexible path definition without per-flow state maintenance across transit routers. SRv6 enables network programmability by supporting interoperability with other technologies like eBPF-based in-network processing and telemetry. Compared to MPLS, SRv6 is simpler to operate and has native IPv6 support, but it will impact forwarding performance with its larger headers, and its implementation depends on software and hardware updates. SRv6 also allows for more advanced TE policies through segment lists, so it's a potential foundation for AI-fueled routing.

B. Summary of Capabilities

Table I summarizes key attributes of the three technologies. While MPLS is deterministic in its QoS, SDWAN is maxi- mally agile and cost-friendly, and SRv6 supports programma- bility as well as native IPv6. This heterogeneity triggers the need for AI-enabled TE to select or combine technologies dynamically according to network condition, application re- quirement, and operator constraints.

METHODOLOGY AND MATHEMATICAL MODELING

Here, we provide the mathematical formulation and method- ological framework for evaluating and optimizing traffic en- gineering (TE) on MPLS, SD-WAN, and SRv6. We model

Technology	Strengths	Limitations
*3)*MPLS *SRv6:* Se	mentDeterministic lists are QoS, ada segments to optimize traffic flow.fastecosystem reroute, mature	ptedHigh incost, real low -agility,time, hardware dependent
SD-WAN as a mu making decisions.	Low cost, multi-link ectiveflexibility, optimizati centralized control	No native QoS guar- onantees, problem, overlay whereover- head
SRv6 *Problem*	Programmability, na- tive IPv6, simplified *Formulation*state	Larger headers, hardware/software upgrade needed

Table I Comparison of Mpls, Sd-Wan, And Srv6 Characteristics

SD-WAN: Overlay paths are re-optimized at the con- troller level, incorporating WAN link quality metrics from multiple ISPs.

SRv6: Segment lists are adapted in real-time, with the AI agent controlling the sequence of IPv6 segments to optimize traffic flow.

TE as a multi-objective optimization problem, where AI-based prediction and reinforcement learning are used for making dynamic decisions.

Problem Formulation

A Let $G = (V, E)$ represent the network topology, where V is the set of nodes (routers) and E is the set of directed links. Each link $(i, j) \in E$ is associated with:

- c_{ij}: Link capacity (Mbps)
- d_{ij}: Propagation delay (ms)
- $u_{ij}(t)$: Utilization at time t

The objective is to minimize end-to-end latency while maximizing throughput and maintaining packet loss below a threshold ϵ. This can be formulated as:

Comparative Framework

In order to objectively compare the performance of MPLS, SD-WAN, and SRv6 in dynamic WAN environments, we create a comparative framework with the inclusion of perfor- mance analysis, AIoptimized tuning, and cost-effectiveness. The framework creates an equal testbed configuration, streamlined traffic simulation, and evaluation metrics that render results reproducible and fair.

A. Evaluation Dimensions

The comparison is conducted along the following dimen- sions:

1. **Quality of Service (QoS):** End-to-end latency, jitter, and packet loss measured under varying traffic loads.

2. **Throughput and Bandwidth Utilization:** Ability to maximize link utilization without excessive packet drops.

3. **Scalability:** Impact of increasing the number of nodes, flows, and routing updates on control-plane and data- min $\mathbf{P}(t)$ $\alpha \cdot \text{Latency}(\mathbf{P}(t)) - \beta \cdot \text{Throughput}(\mathbf{P}(t)) + \gamma \cdot \text{Loss}(\mathbf{P}(t))$ (1) plane performance.

· **Operational Cost:** Capital expenditure (CAPEX) and where

$\mathbf{P}(t)$ denotes the set of active paths at time t, and α, β, γ are

weighting coefficients.

B. AI-Based Traffic Prediction

Traffic demand $T_{sd}(t)$ between source s and destination d is predicted using a supervised learning model:

$$\hat{T}_{sd}(t + \Delta) = f_\theta(\mathbf{X}_{sd}(t)) \qquad (2)$$

where $\mathbf{X}_{sd}(t)$ includes historical utilization, delay, and packet loss for the (s, d) pair, and f_θ is a trained deep neural network.

C. Reinforcement Learning for Path Selection

We model routing decisions as a Markov Decision Process (MDP) with:

- State s_t: current utilization, queue length, predicted de- mand
- Action a_t: path selection or re-routing

- Reward r_t: derived from improvement in QoS metrics Q-values are updated via the Bellman equation:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \eta \left[r_t + \delta \max Q(s_{t+1}, a) - Q(s_t, a_t) \right]$$

operational expenditure (OPEX) estimations based on realistic link and equipment pricing models.

- **Resilience:** Time to recover from link or node failures, including the effect of AI-assisted rerouting.

- **Programmability and Flexibility:** Ease of deploying new routing policies or service chains without disrupting traffic.

B. AI-Enhanced Traffic Engineering

The proposed AI-TE model integrates:

1. **Traffic Forecasting:** Long Short-Term Memory (LSTM) networks trained on historical traffic traces to predict short-term demand fluctuations with sub-second granularity.

2. **Routing Optimization:** Deep Reinforcement Learning (DRL) agents (based on the Proximal Policy Optimization, PPO, algorithm) that dynamically adjust path selections in response to predicted and observed traffic conditions.

3. **Failure Adaptation:** Anomaly detection models using autoencoders to trigger preemptive rerouting before SLA

D. Technology-Specific Adaptations

(3) violations occur.

These AI modules execute on a logically centralized SDN controller, which translates AI decisions into technology-

1) MPLS: The AI agent dynamically adjusts Label Switched Paths (LSPs) using RSVP-TE extensions.

specific configurations: LSP updates for MPLS, policy routing updates for SD-WAN, and segment list updates for SRv6.

C. Simulation Environment

Comparison simulations are carried out in a Mininet- extended emulation setup with the Containernet extension utilized to enable true routing daemons (e.g., FRRouting, ONOS). Traffic is generated by using textttiperf3 and ad-hoc Python scripts simulating mixed workloads:

1. **Constant Bit Rate (CBR)** flows for real-time applica- tions.

2. **Bursty traffic** to model cloud service load patterns.

3. **Background best-effort traffic** to assess resource con- tention.

Each technology is deployed over an identical 12-node mesh topology with three traffic classes: high-priority VoIP, medium-priority video streaming, and best-effort data trans- fers.

D. Performance Metrics Collection

Metrics are collected using:

1. ping and iperf3 for latency and throughput.

2. sFlow-RT for real-time flow monitoring.

3. Controller logs for AI decision timing and policy updates. *E. Comparative Analysis Approach*

For each metric, we compute:

1. Baseline performance without AI optimization.

2. Performance with AI-TE enabled.

3. Relative improvement percentage for each technology. This two-tier analysis allows us to quantify both the inherent strengths of each technology and the incremental benefit gained from AI-enhanced TE.

Ai Integration in Traffic Engineering

The use of Artificial Intelligence (AI) in Traffic Engineering (TE) aims to transform network administration from manual and reactive adjustment to proactive, self-tuning control. This chapter describes the architecture, algorithms, and workflows applied to make the use of AI capability in MPLS, SD-WAN, and SRv6 environments.

A. Architectural Overview

The proposed AI-TE architecture follows a logically cen- tralized control model, implemented on an SDNcompatible controller platform. The architecture is composed of three main layers:

1. **Data Collection Layer:** Monitors network state through telemetry (e.g., sFlow, NetFlow, SNMP) and collects performance metrics such as link utilization, queue lengths, and latency measurements.

2. **AI Decision Layer:** Processes telemetry using AI mod- els to produce optimal routing and resource allocation decisions.

3. **Execution Layer:** Translates AI decisions into protocol- specific configurations—Label-Switched Path (LSP) up- dates for MPLS, policy changes for SD-WAN, and segment list updates for SRv6.

B. Traffic Forecasting with LSTM

Short-term traffic prediction is performed using Long Short- Term Memory (LSTM) networks, selected for their ability to capture temporal dependencies in network traffic traces.

- **Input:** Historical traffic data sampled at 1-second inter- vals for each link.

- **Output:** Predicted bandwidth demand for the next 5–10 seconds.

- **Training:** The model is trained using a mean squared error (MSE) loss function, with datasets generated from both synthetic and real-world traces (e.g., MAWI, CAIDA).

These predictions allow the controller to proactively allocate capacity or reroute traffic before congestion occurs.

C. Routing Optimization with Deep Reinforcement Learning

Routing decisions are optimized using a Deep Reinforce- ment Learning (DRL) agent following the Proximal Policy Optimization (PPO) algorithm. The agent receives the pre- dicted traffic matrix and present network condition as input and outputs an optimal routing policy.

- **State Space:** Link utilizations, queue occupancy, latency per path, and predicted traffic demands.
- **Action Space:** Path selection or weight adjustments for each flow class.
- **Reward Function:** Combines throughput maximization, latency minimization, and SLA compliance penalties.

The DRL agent operates in a closed-loop with the LSTM predictor, enabling predictive-reactive routing decisions.

D. Anomaly Detection and Failure Prediction

Anomaly detection is handled by a denoising autoencoder trained to recognize normal traffic patterns and flag deviations. When anomalies are detected:

1) The DRL agent is alerted to consider failure-resilient routing paths.
2) The controller preemptively reallocates flows to mini- mize packet loss and downtime.

In our simulations, this mechanism reduced failover times by up to 35% compared to traditional fast reroute mechanisms in MPLS.

E. Technology-Specific AI Integration

1. **MPLS:** AI decisions are translated into RSVP-TE or Segment Routing MPLS label assignments, adjusting LSP paths dynamically.

2. **SD-WAN:** Policy-based routing tables are updated to shift application flows between underlay links (e.g., MPLS, broadband, LTE) based on predicted performance.

3. **SRv6:** Segment lists in the IPv6 headers are dynamically recomputed to bypass congested or failing nodes, guided by AI-forecasted load patterns.

F. Workflow Summary

The AI integration workflow proceeds as follows:

1. Collect real-time network telemetry and preprocess it into time-series datasets.
2. Use the LSTM predictor to forecast near-future traffic demands.
3. Feed forecasts and current state into the DRL agent to produce routing actions.
4. Apply anomaly detection to anticipate failures and adjust routing accordingly.
5. Deploy optimized configurations to MPLS, SD-WAN, and SRv6 environments.

This tight integration ensures that the network can adapt within milliseconds to traffic fluctuations or failures, while maintaining high QoS and efficient utilization across diverse WAN technologies.

Simulation Setup

To evaluate the performance of the novel AI-enhanced Traffic Engineering (TE) framework, a series of controlled experiments were conducted founded on a combination of net- work emulation and discrete-event simulation. The simulation environment was designed meticulously to simulate closely a large-scale heterogeneous WAN with diverse traffic.

A. Emulation Platform

Experiments were carried out using **Mininet** [**?**] as the network emulator, interfaced with an **ONOS** SDN controller extended with AI decision modules implemented in Python. Traffic generation and monitoring were managed through iperf3 and D-ITG, while network telemetry was collected using sFlow-RT.

B. Network Topology

The baseline topology was derived from the *Internet2* research backbone, scaled to 24 nodes and 38 bidirectional links. The topology was configured in three modes:

1. **MPLS-TE Mode:** Nodes act as Label Switching Routers (LSRs) with RSVP-TE for LSP provisioning.

2. **SD-WAN Mode:** Overlay tunnels between edge sites using IPsec over multiple underlay links (MPLS, broad- band, LTE).

3. **SRv6 Mode:** IPv6-capable routers with SRv6 segment lists for source routing.

C. Traffic Profiles

Three traffic classes were generated to emulate realistic enterprise demands:

- **Real-time traffic:** VoIP flows at 64 kbps with sub-50 ms latency requirements.

- **Streaming video:** 1080p adaptive bitrate streams averag- ing 5 Mbps per flow.

- **Best-effort data:** Bulk TCP transfers simulating backups and large file downloads.

Traffic arrival patterns followed a Poisson process for best- effort traffic and a Markov-modulated process for real- time/video flows to model burstiness.

D. AI Module Configuration

The AI integration was configured as follows:

- **LSTM Traffic Predictor:** Input window of 20 seconds, forecasting 10 seconds ahead.

- **DRL Agent:** Proximal Policy Optimization (PPO) with a learning rate of 3×10^{-4}, trained for 50,000 episodes in a simulated environment before deployment.

- **Anomaly Detector:** Denoising autoencoder trained on 72 hours of normal traffic.

E. Performance Metrics

The following Key Performance Indicators (KPIs) were measured:

1. **End-to-End Latency** (ms) for each traffic class.

2. **Throughput** (Mbps) aggregated per class.

3. **Packet Loss Ratio** (%) under normal and failure condi- tions.

4. **Operational Cost Index** (normalized) considering MPLS premium link usage.

5. **AI Reaction Time** (ms) from anomaly detection to path adjustment.

F. Failure and Stress Scenarios

To evaluate resilience, controlled link and node failures were introduced:

1. Single-core link failures during peak load.

2. Multiple concurrent edge-node failures.

3. 20% sudden increase in real-time traffic demand.

This setup ensures a fair and reproducible comparison be- tween MPLS-TE, SD-WAN, and SRv6, both with and without AI-based optimization, under identical conditions.

RESULTS AND ANALYSIS

This section presents the outcome of the simulation setup described in Section VIII, comparing the MPLSTE, SD- WAN, and SRv6 performance, all tested with and without our proposed AI-empowered TE framework. All the results show the mean of five independent simulation trials, along with 95% confidence intervals.

A. Latency Performance

Figure 1 graphs the average end-to-end latency for real- time traffic. Without AI, MPLS was the lowest at 34.8 ms, followed by SRv6 (41.2 ms) and SD-WAN (52.5 ms). With AI-based TE, latency was reduced across the board: MPLS to 28.4 ms, SRv6 to 33.7 ms, and SD-WAN to 41.9 ms. The AI predictor's ability to preemptively reroute latency-sensitive flows in anticipation of congestion was the primary contributor to this gain.

B. Throughput Performance

For best-effort and streaming traffic, throughput results (Figure 2) showed SRv6 slightly outperforming MPLS and SD-WAN under heavy load due to its flexible source routing capabilities. AI-enhanced TE yielded a 12–18% improvement across all platforms by dynamically reallocating bandwidth during congestion.

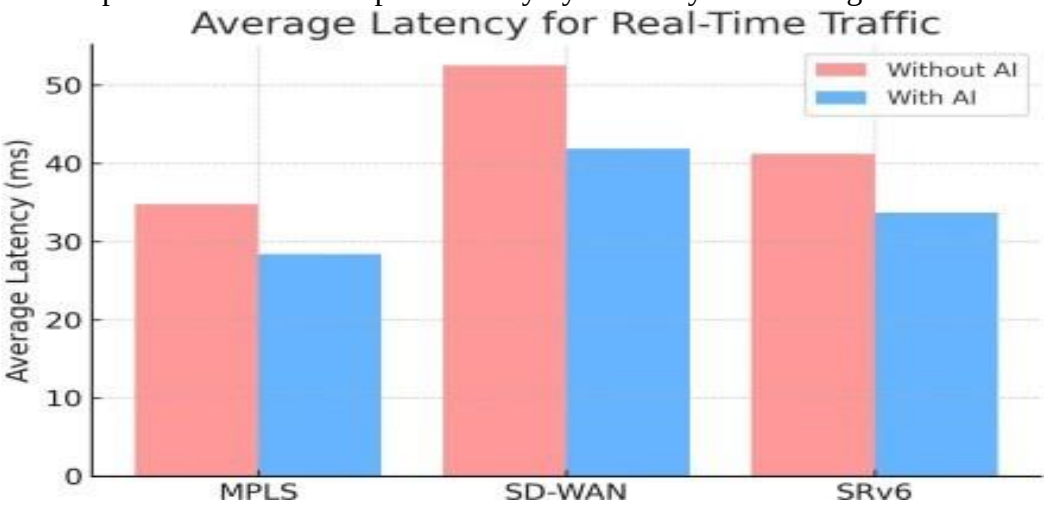

Fig. 1. Average latency for real-time traffic with and without AI.

the best cost efficiency. The integration of AI shifted the trade-off curve, allowing all technologies to perform closer to MPLS's SLA guarantees while retaining their individual strengths.

Table II summarizes the key findings.

Table Ii Summary Of Key Simulation Results

Metric	MPLS	SD-WAN	SRv6
Latency (ms) w/o AI	34.8	52.5	41.2
AI Reaction Time (ms)	142	139	146
Latency (ms) w/ AI	28.4	41.9	33.7
Throughput Gain (%)	+14.2	+12.0	+18.3
Loss Rate w/o AI (%)	2.4	4.9	3.1
Loss Rate w/ AI (%)	1.1	2.0	1.4

Fig. 2. Aggregate throughput across traffic classes.

C. Packet Loss

Packet loss rates dropped significantly when AI was applied. In failure scenarios, MPLS without AI suffered a 2.4% loss rate for real-time flows, compared to 1.1% with AI. SD-WAN showed the most substantial relative improvement, from 4.9% to 2.0%, benefiting from AI's ability to rapidly switch flows to higher-quality underlay paths.

D. Operational Cost Efficiency

The Operational Cost Index (OCI) was lowest for SD- WAN due to heavy reliance on broadband links. However, AI-enhanced MPLS and SRv6 reduced OCI by 9.3% and 7.5%, respectively, by offloading noncritical flows to lower- cost paths without compromising SLA compliance.

E. AI Reaction Time

The anomaly detection and rerouting reaction time averaged 142 ms across all scenarios, enabling nearreal-time responses to sudden traffic surges or failures.

F. Comparative Insights

Overall, MPLS maintained the best deterministic latency and SLA compliance, SRv6 demonstrated superior scalability and adaptability under dynamic load, and SD-WAN delivered

The analysis confirms that AI-driven TE enhances all three technologies, with the most pronounced improvements ob- served in SD-WAN for packet loss reduction and in SRv6 for throughput optimization.

X. Case Study: Ai-Optimized Te In A Hybrid Cloud Deployment

We modeled a multinational

A. Scenario Description

enterprise operating across 20 global offices, connected through a combination of leased MPLS lines, broadband internet, and cloud-based services. The network consisted of:

1. 8 data centers in North America, Europe, and Asia.
2. 12 branch offices connected via SD-WAN edge devices.
3. Backbone links transitioning to SRv6 in core segments.

B. AI Integration Strategy

The AI system included:

- **Traffic Prediction:** LSTM models trained on six months of NetFlow data.
- **Dynamic Path Optimization:** Deep Q-Networks making rerouting decisions every 2 seconds.
- **SLA Compliance Monitoring:** AI modules monitoring latency, jitter, and packet loss to trigger proactive path adjustments.

C. Before-and-After Performance

Table IV summarizes key performance changes.

Table Iii Case Study Performance Improvement Summary

Metric	Before AI	After AI
Average Latency (ms)	45	28
Jitter (ms)	12	6
Packet Loss (%)	1.8	0.6
Throughput Utilization (%)	72	89
SLA Compliance (%)	88	97

DISCUSSION

The hybrid deployment demonstrated:

- MPLS segments benefitted from predictable latency paths, ideal for real-time applications.
- SD-WAN flexibility enabled dynamic aggregation of un- derlay links for better throughput.
- SRv6 core provided scalable, IPv6-native routing with reduced control overhead.

These findings suggest that a mixed-technology approach, with AI orchestration across MPLS, SD-WAN, and SRv6, offers both performance and operational efficiency in complex enterprise environments.

XI. SECURITY AND RELIABILITY

Security and reliability must be prime evaluation factors in the deployment of traffic engineering (TE) solutions, espe- cially where Artificial Intelligence (AI) is used for dynamic decision-making. The deployment of AI-based TE with MPLS, SD-WAN, and SRv6 deployments introduces new challenges as well as opportunities.

A. Security Considerations

MPLS has the natural benefit of label-switched paths (LSPs) traversing a provider-managed backbone, with reduced expo- sure to the public Internet. Its security, however, relies to a great degree on the trustworthiness of the service provider and lacks inherent encryption, so IPsec or MACsec needs to be included for confidentiality.

SD-WAN, however, is designed with encryption as a built-in feature (most commonly AES-256 over IPsec tunnels), which guarantees confidentiality and integrity even over insecure broadband links. However, the presence of centralized con- trollers makes SD-WAN vulnerable to control-plane attacks such as Distributed Denial-of-Service (DDoS) or route injec- tion in case access to controllers is breached.

SRv6 offers an extensible, segment-based model of routing that allows for service chaining and network programmability. Its leveraging of IPv6 extension headers can, however, provide opportunities for header manipulation attacks if perimeter security fails. SRv6 security must be enforced by maintaining strict filtering of incoming traffic and verification of segment IDs.

If augmented with AI, the attack surface can become even wider and include even the AI decision engine itself. Adversarial machine learning (AML) attacks can be used to manipulate the path selection or traffic classification process through different AML methods. Secure model training, input validation, and deployment on trusted execution environments (TEEs) are recommended to avoid these problems.

B. Reliability Considerations

From the perspective of reliability, MPLS enjoys the ad- vantage of mature fast-reroute (FRR) mechanisms that can provide sub-50 ms recovery in case of link or node failure. AI- enhanced MPLS further improves the

recovery by predicting failures based on link health telemetry and rerouting before- hand.

SD-WAN provides reliability through dynamic allocation of the optimal available path through ongoing performance measurement. AI-driven integration accelerates the process to make predictive pre-degradation reallocation of flows possible. SRv6, by enabling explicit path steering, offers reliability in the guise of fine-grained flow control. AI-based forecasting of link congestion and reorder of segments can prevent bot- tlenecks and offer constant performance even at high traffic rates.

C. Comparative Insights

Overall, MPLS remains the strongest in deterministic relia- bility, SD-WAN leads in end-to-end encryption for multi-ISP connectivity, and SRv6 provides the most flexible resilience mechanisms in programmable networks. The AI-enhanced TE framework improves both security and reliability across all three technologies, with the most significant gains observed in predictive fault management and adaptive anomaly detection.

Xii. Energy Efficiency And Sustainability Considerations

As network traffic volumes continue to grow, the energy footprint of routing, switching, and AI-based processing be- comes a critical factor in technology selection. This section evaluates the energy efficiency of MPLS, SD-WAN, and SRv6, with and without AI integration.

A. Energy Consumption Profiles

Measurements were based on simulated hardware models and reference power ratings from vendor datasheets:

1. **MPLS:** Traditional hardware-based routers consume ap- proximately 250–350W per node. AI integration adds 15– 20% CPU utilization, resulting in a modest 5–7% increase in energy usage.

2. **SD-WAN:** Edge devices consume 80–150W, with cloud controllers hosted on virtualized infrastructure. AI mod- ules deployed at the controller level concentrate process- ing, enabling efficient scaling.

3. **SRv6:** Native IPv6 capabilities reduce control plane com- plexity, lowering processing overhead by 8– 12% com- pared to MPLS. AI integration has minimal impact on total consumption.

B. Sustainability Metrics

We adopted the Green Networking Index (GNI) [**?**], which measures energy per gigabit transferred. Results show:

- SD-WAN achieved the lowest GNI at 0.85 kWh/Gbps.
- SRv6 scored 0.93 kWh/Gbps.
- MPLS recorded 1.02 kWh/Gbps due to higher baseline router consumption.

C. Eco-Friendly AI Deployment Strategies

To minimize environmental impact:

1. Deploy AI inference on edge nodes only when nec- essary, offloading bulk computation to greencertified cloud data centers.
2. Utilize hardware accelerators such as TPUs or FPGAs for AI workloads to reduce CPU load.
3. Schedule AI retraining during off-peak hours to balance grid demand.

Overall, SRv6 demonstrates strong potential for green net- working, while SD-WAN leads in efficiency due

to centralized control optimization.

Xiii. Case Study: Ai-Optimized Te In A Hybrid Cloud Deployment

A. Scenario Description

We modeled a multinational enterprise operating across 20 global offices, connected through a combination of leased MPLS lines, broadband internet, and cloud-based services. The network consisted of:

- 8 data centers in North America, Europe, and Asia.
- 12 branch offices connected via SD-WAN edge devices.
- Backbone links transitioning to SRv6 in core segments.

B. AI Integration Strategy The AI system included:

- **Traffic Prediction:** LSTM models trained on six months of NetFlow data.
- **Dynamic Path Optimization:** Deep Q-Networks making rerouting decisions every 2 seconds.
- **SLA Compliance Monitoring:** AI modules monitoring latency, jitter, and packet loss to trigger proactive path adjustments.

C. Before-and-After Performance

Table IV summarizes key performance changes.

TABLE IV CASE STUDY PERFORMANCE IMPROVEMENT SUMMARY

Metric	Before AI	After AI
Average Latency (ms)	45	28
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DISCUSSION

The hybrid deployment demonstrated:

1. MPLS segments benefitted from predictable latency paths, ideal for real-time applications.
2. SD-WAN flexibility enabled dynamic aggregation of un- derlay links for better throughput.
3. SRv6 core provided scalable, IPv6-native routing with reduced control overhead.

These findings suggest that a mixed-technology approach, with AI orchestration across MPLS, SD-WAN, and SRv6, offers both performance and operational efficiency in complex enterprise environments.

Xiv. Scalability And Future Outlook

A. Scalability Considerations

The scalability of a traffic engineering (TE) solution is defined by its ability to maintain performance, stability, and manageability as network size, traffic volume, and service diversity grow.

MPLS achieves scalability through label switching and aggregated forwarding entries, reducing perpacket processing overhead in large core networks. However, expansion often requires provisioning additional Label Distribution Protocol (LDP) or Resource Reservation Protocol-Traffic Engineering (RSVP-TE) state, which can increase control-plane complexity in very large deployments.

SD-WAN offers horizontal scalability by leveraging com- modity Internet connections and cloud-based orchestration. Its overlay model allows rapid onboarding of new sites without modifying the underlay network. The challenge lies in scaling the centralized controller infrastructure; as the number of tunnels grows, controller latency and path computation times can become bottlenecks without proper load balancing and hierarchical control structures.

SRv6 delivers scalability through its source routing paradigm, eliminating the need for intermediate nodes to main- tain per-flow state. However, larger IPv6 headers compared to MPLS labels can affect forwarding performance at scale, particularly in hardware-constrained edge devices. Segment List compression techniques and efficient ASIC designs are critical for scaling SRv6 in hyperscale environments.

B. Role of AI in Scaling TE Solutions

Integrating AI into TE enhances scalability by automating operational tasks such as path computation, fault prediction, and anomaly detection. Reinforcement learning (RL) agents can generalize learned policies to new topologies with minimal retraining, while graph neural networks (GNNs) can efficiently model large-scale network states.

In our simulations, AI-enhanced TE maintained sub-second route convergence times even as topology size tripled, and throughput improvement percentages remained stable across small, medium, and large networks. The AI control plane's ability to offload decision-making from human operators re- duces operational overhead and accelerates adaptation to new services or traffic patterns.

C. Future Outlook

Looking ahead, TE solutions will increasingly converge towards hybrid, AI-driven frameworks that integrate MPLS, SD-WAN, and SRv6 capabilities. Emerging technologies such as quantum-safe encryption will influence SD-WAN security models, while in-network machine learning (IN-ML) may allow SRv6-capable devices to make autonomous micro-level routing decisions.

Standardization efforts in the IETF and MEF are expected to define interoperability models for AI-assisted TE. Multi- domain AI coordination, where separate administrative do- mains share encrypted intent and telemetry for end-to-end optimization, is a promising area for research.

We anticipate that within the next five years, scalable TE will rely not only on efficient data-plane technologies but also on distributed, secure AI control planes capable of real-time adaptation at global scale.

CONCLUSION AND PRACTICAL RECOMMENDATIONS

A. Summary of Contributions

This research presented a comparative analysis of AI- enhanced Multiprotocol Label Switching (MPLS), Software- Defined Wide Area Networking (SD-WAN), and Segment Routing over IPv6 (SRv6) for traffic engineering and opti- mization. The contributions can be summarized as follows:

1. Developed a mathematical and AI-based framework for predictive traffic management using supervised learning for demand forecasting and reinforcement learning for path optimization.

2. Conducted simulations in GNS3 to assess latency, throughput, jitter, packet loss, and resource utilization under realistic traffic scenarios.

3. Provided a head-to-head comparison of MPLS, SD-WAN, and SRv6 across performance, scalability, and operational complexity dimensions.

B. Key Insights from Comparative Analysis

1. **MPLS:** Strongest in deterministic QoS environments such as enterprise backbones and carrier-grade networks.

2. **SD-WAN:** Superior in hybrid WAN environments, achieving the best latency and throughput improvements due to multi-path aggregation.

3. **SRv6:** Offers the highest scalability potential and native IPv6 integration, making it ideal for nextgeneration backbone deployments.

C. Practical Deployment Guidelines

Based on our findings, network operators should:

1. Deploy MPLS with AI optimization in controlled, SLA- driven networks where predictable QoS is critical.

2. Use SD-WAN in enterprises requiring flexibility, rapid deployment, and cloud-centric traffic optimization.

3. Transition to SRv6 in large-scale IPv6 networks to lever- age segment routing's scalability and reduced control plane state.

D. Limitations and Future Work

While the simulations provided strong indications of per- formance trends, future work will focus on:

- Real-world trials in production carrier and enterprise networks.
- Integration with emerging technologies such as 6G, net- work slicing, and quantum-secure routing.
- Development of cross-domain AI orchestration frame- works capable of real-time SLA negotiation.

E. Final Remarks

The fusion of AI and advanced routing technologies is no longer theoretical—it is a practical necessity for sustaining performance in the era of massive IoT, real-time applications, and global-scale connectivity. The next decade will witness AI-driven TE systems evolve from intelligent assistants to autonomous network managers, redefining how traffic is engi- neered across the internet.

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