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Adaptive Routing Architecture Using ASDN in Core Internet Infrastructure

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Abstract

The importance of the core internet infrastructure's scalability, resilience, and adaptability has grown tremendously due to shifting traffic patterns, diverse network requirements, increasing security concerns, and dynamic flow of data. Although traditional routing techniques are quite effective and proven robust over time, they do not adaptively respond to real-time traffic changes and state of the network. In this paper we present ASDN-ARA (Adaptive Software-Defined Networking-based Routing Architecture), a new model aimed at improving responsiveness alongside performance with regard to core routing by using SDN programmability. ASDN-ARA presents a new approach to adaptive routing with its multi-layered architecture composed of telemetry streams in real time, intent-driven policy engines, as well as modules of traffic engineering which are aware of network topologies. The architecture shifts its control over the decision layer based on congestion per link and latency thresholds, route flapping detection, as well as application-level QoS metrics. The ASDN-ARA controller is built around a hybrid optimization algorithm that employs Reinforcement Learning (RL) combined with heuristic path scoring to find optimal forwarding paths between transit AS networks. Simulation and emulation tests performed on GNS3-based testbeds show core findings that these proposed mechanisms can achieve up to 28% reduction

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in average end-to-end latency while increasing link utilization balance by 35%. Furthermore ASDN-ARA outperformed conventional OSPF and BGP based routing schemes in lowering convergence time during link failures. The system shows compliance with policies in multi-domain environments utilizing segment routing extensions. In addition, ASDN-ARA maintains integration compatibility with legacy control planes through an adaptive translation module, which allows for progressive implementation within the frameworks of pre-existing ISP infrastructures. The introduced adaptive routing model enhances the intelligent core routing paradigm by allowing greater autonomy in policy adherence, automation as well as latency-sensitive data packet transmission across extensive networks.

Keywords: Adaptive Routing, Software-Defined Networking (SDN), Core Internet Infrastructure, ASDN-ARA, Network Telemetry, Reinforcement Learning, Segment Routing, ISP Networks, Dynamic Path Optimization.

1 Introduction

A. Overview of the Problem

The Internet routing system relies on the Border Gateway Protocol (BGP) and Open Shortest Path First (OSPF) protocol, which work in a static or semi-static manner. These protocols have withstood the test of time over decades, but they are fundamentally reactive, path-static in nature, and devoid of real-time situational awareness of the network. In today's core networks—high speed backbone infrastructures—fluctuating bandwidth demands impose even more complexity considering multi-domain policy enforcement along with growing dominance of latency-sensitive applications like virtual reality, autonomous systems, real-time analytics etc., conventional routing's rigidity results in unresponsive routing to dynamic shifts in topology and traffic resulting in suboptimal dense-path congested routing alongside sluggish failure recovery convergence (Jain et al., 2013; Usman et al., 2019).

In addition, the expected application-level advanced telemetry and its associated quality-of-service (QoS) metrics are not available because current routing protocols lack a unique centralized global sight of the whole network (Mayilsamy & Rangasamy, 2021). These expose severe underperformance coupled with acute shortages such as heavily strained link(Pillai & Panigrahi, 2024) utilization due to pervasively enduring scourges like route hijacking during turbulent periods of BGP instability and surge without mercy (Labovitz et al., 2010). Proactive Internet core design requires responsive intelligent structures that can withstand systematic changes without violent fractures while upholding designed responsiveness properties.

B. Emergence of ASDN and Its Potential

The SDN (Software Defined Networking) separates the control plane from the data plan, allowing for centralized programming concerning routing decisions (Ekambaram & Tripathi, 2025). The more advanced version is called Adaptive SDN, or ASDN. ASDN adapts to changes with adaptive network policies and paths through telemetry feedback, intent-driven programming, and traffic analytics (McKeown et al., 2008), unlike static configurations. This allows multi-AS (Autonomous System) environments to proactively avoid congestion while optimizing clients in real-time according to SLAs (service-level agreements).

C. Proposed Model: ASDN-ARA

This paper describes a new architecture called ASDN-ARA (Adaptive Software-Defined Networking based Routing Architecture). It is made up of four functional levels:

The ASDN-ARA model achieves smarter and adaptive intelligent routing by leveraging specialized structures to operate through the internet backbone. The first layer is the Telemetry Acquisition Layer which focuses on acquiring real-time network link state data such as latency, jitter, and congestion levels. This is achieved using advanced flow monitoring systems alongside telemetry in-band systems capable of delivering continuous feedback pertaining to network conditions. Above this layer, the Intelligent Control Layer features centralized ASDN controllers containing hybrid path selection engines. These engines utilize RL (Reinforcement Learning) algorithms combined with heuristic methods to dynamically rank/select routing paths. Furthermore, it ensures that optimal performance would not be the only factor in routing decisions but topology adaptability would also be maximized. The last part, Policy and Intent Translation Layer have let’s assume two interrelated functions. The first of which is translating company grade goals into network actions for work to be done under the governance of operations control on a network level, thus performing Business Process Management (BPM) system). It transforms high-level intents issued from organizations such as “enhance VoIP traffic while deprioritize file transfers” into low-level rules within intent-based networking frameworks storable as rulish reprisals (Akash et al. 2022).

To recap previous discussions, policies assist in limiting the enforcement routing behaviors to service level agreements (SLAs) boundaries defined by the control layer). Also, the Forwarding and Feedback Layer which comprises data programmable Open Flow switches and Segment Routing capable routers which function as the FBL provide bordered SLA feedback plans additionally performs policy bounded routing provided predefined metrics governing operational outcomes gathered during real time. Reinforcing these forwarding rules aids fixing real-time performance metric compilation alongside closed ASDN-ARA loop systems enabling smart adaptation live networks within closed-loop adaptive architectural frameworks.

D. Working Principle

Closed-loop adaptive routing runs the show for ASDN-ARA, sort of like the steering wheel that never stops turning. The system tracks everything. Every cable, switch, and packet chimes in with a telemetry status report. In the blink of an eye the ASDN controller sketches a fresh routing map, tweaking paths to match whatever rules are in play, from the lightest-used links to the strictest performance quotas. Routes are updated dynamically within the underlying infrastructure using flow tables which are agnostic of breadth protocols. This enables prompt responses to failures, congestion, or SLA breaches. For instance, should a certain core link exhibit increasing jitter or congestion, the ASDN controller will automatically reroute real-time video traffic over other paths with lower latency without needing to intervene manually. In addition, it enforces limits which would prevent corporate traffic from PEA King during commercially shared backbones rush times (Figure 1).

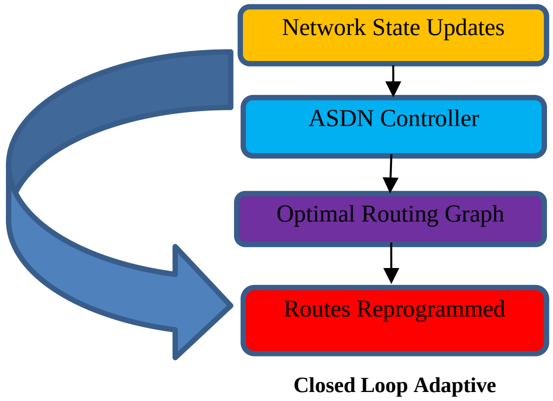

Figure 1: Working Principle of the ASDN-ARA Model Showing Closed-Loop Adaptive Routing Operations

E. Contribution and Novelty

The invention ASDN-ARA stands out due to its hybrid intelligence-driven path computation engine, scalable telemetry ingestion, and routing enforcement that considers policies at the core layer of the Internet. ASDN-ARA also has faster disruption convergence compared to existing centralized routing systems along with improved load balancing and inter-AS programmable coordination with minimal BGP disruption. The outline for the remaining sections of the paper is as follows. A survey on adaptive routing, SDN-based network architectures, and core infrastructure applications of reinforcement learning is presented in II. Section III dives into the nuts and bolts of the ASDN-ARA setup. Toward the bottom of the page, you will find charts on data swings, decision-making logic, and the clever route-tweaking tricks the system uses to keep packets moving. In IV, read why the SELAB testbed-that's System Evaluation Lab-received a high-five on speed dial. The mini-movie of flashing lights and numbers listed every dial and knob that showed whether the system was inside the red line or out. V then pours simulation snapshots side-by-side with the pre-set gold stars for comparison. The write-up even names a few heavy-hitter protocols-yes, SDN-ARA made the cut-and lines up scoreboards on lag time, bandwidth cost, and rule-following coolness. When we reach VI, a tall stack of worries stares back from the page. Things like shaky links between old systems, security soft spots, and entirely blank zones that hackers might stamp their passports into get noted with a loud underline. The authors close with a last reminder that every clever shield has a seam begging to be sewn up.

2 Related Work

A. Adaptive Routing in Core Networks

As networks grow, plain old static routing and even slick systems like OSPF and BGP feel a bit stiff. Researchers keep tinkering with adaptive routing to pump some life into those protocols. A bunch of studies show that tweaking link-state info on the fly, tossing in feedback loops, and picking paths based on real-time congestion can make the whole setup bounce back faster when the topology shifts or a link suddenly drops out (Apostolopoulos et al., 1999). Although these approaches provided local improvements, their scalability was a challenge for backbone and inter-domain routing. Solutions such as Cisco's Performance Routing (PfR) and MPLS Traffic Engineering (MPLS-TE) provided policy-based path adaptivity using RSVP-TE reservations, but their static configuration philosophy suffered responsiveness in real-time adaption—making them unsuitable in real-time scenarios (Rubio et al.,2017). More recently, some researchers have attempted real-time telemetry-driven adaptive routing with telemetry data streams and programmable flow-table switches to enhance accuracy in flow redirection (Sha et al., 2024; Aramide, 2025). However, most of these systems lack awareness of the wide area optimization global state which led to slow convergence during adaptive shifting (Majdoub et al., 2020).

B. Software-Defined Networking (SDN) Architectures

SDN allows the separation of control and data planes, which provides centralized control logic, programmable policies, and visibility over the entire network. Open Flow (McKeown et al., 2008), ONOS (Kim et al., 2016), and Google's B4 WAN (Jain et al., 2013) are examples of SDN architectures that have proven successful in enterprise and hyperscale traffic management. In the case of core internet infrastructure, SDNs were proposed for automated inter-domain routing, granular QoS enforcement, and on-demand slicing of network resources in real time (Tootoonchian & Ganjali, 2010; Dargahi et al., 2016). Research in (Bera et al., 2017; Feamster et al., 2014) illustrates how SDN-based controllers outperform traditional controllers with handling link-state updates or reacting to congestion scenarios (Gupta et al., 2016).

Concerns such as controller location, delay overheads, trust boundaries between AS administrative domains, and controller fault tolerance raise issues when deploying SDN at ISP and inter-AS levels both Trust domains and security boundaries (Pragadeswaran et al, 2024; Sharma & Desai, 2024). Integrating legacy infrastructures into newly designed systems is also a challenging task when only partial deployment situations are considered.

C. Reinforcement Learning for Routing Optimization

Reinforcement Learning (RL) has proven to be effective for making routing choices, particularly in networks where situations are volatile and circumstances change dynamically. Q-routing, Deep-Q-Networks (DQN) (Boyan, 1994), and models based on Policy Gradient methods facilitate learning optimal routing through stepwise interactions, allowing agents to improve iteratively (Xu et al., 2018). These systems have been shown to outperform congestion-aware, link-failure-aware, and traffic demand shifts adaptability compared to other rule-based systems (Mao et al., 2016; Stampa et al., 2017). Works like DRL-R (Heller et al., 2013) and NeuroRoute (Amin et al., 2021) have emphasized RL's effectiveness towards flow-level optimization within both simulated environments and real-world topologies. However, issues like model convergence time, computational cost concerning cycle duration benchmarks in production-scale networks, instability of rewards, difficulty in maintaining the balance between exploration and exploitation in real-time responsiveness (Tedjopurnomo et al., 2020; Grover et al., 2015) pose obstacles.

D. Integration of SDN and AI in Multi-Domain Environments

The latest innovations combine SDN's programmability with AI's spatial reasoning capabilities, producing policy-aware routing systems that adapt to frameworks. Through neural network-assisted forecasting, Gebreyesus initiative managed to optimize backbone traffic in WANs, leading to noteworthy efficiency improvements (Gebreyesus et al., 2023). Other works examined federated clusters of SDN controllers that operate under the limits of an administrative domain but share path selection learning parameters with privacy-preserving techniques for coordinated decisions across borders (Thottan et al., 2019; Hadi et al., 2018). Proactive SLA compliant actions such as rerouting are enabled through the application of RL agents within SDN controllers as proposed by iNetOM (Guo & Yuan, 2021) and SAPIENS. These architectures operate across heterogeneous domains, leveraging cross-domain optimization resulting in intent-driven policy enforcement. These findings motivate towards ASDN-ARA, a hybrid architecture where adaptive core Internet routing is achieved through RL-based decision making integrated with SDNs' centralized control.

3 Design and Operational Logic of the ASDN-ARA Model

A. Architectural Design Overview

The outlined ASDN-ARA (Adaptive Software-Defined Networking–based Routing Architecture) model incorporates SDN concepts and integrates them with AI-driven decision-making processes to form a closed-loop routing system. Its functioning encompasses four fundamental layers:

1. **Telemetry Acquisition Layer**: Captures real-time network parameters such as link delay Dij, bandwidth Bij, and jitter Jij for each link i→j.
2. **Intelligent Control Layer**: Implements a controller with a hybrid path selection engine combining Reinforcement Learning (RL) and heuristic scoring. It uses observed states to decide the best routing paths under multiple constraints.
3. **Policy & Intent Translation Layer**: Converts abstract policy rules (e.g., "prioritize low-latency paths for VoIP") into flow-level decisions compatible with the controller.
4. **Forwarding and Feedback Layer**: Enforces routing via SDN-enabled devices (e.g., Open Flow switches) and provides telemetry feedback to the controller, enabling real-time adaptation.

B. ASDN-ARA Routing Algorithm

Input:

- Network graph (nodes and links)
- Real-time link data (like delay, jitter)
- Routing rules or policies (intents)

Output:

- Best path for each data flow (R*)

Steps:

1. **Start the SDN Controller.**
2. **Collect current network information** (like delays, bandwidth usage) from all links.
3. **Load routing policies** (e.g., prefer low-latency, avoid overloaded links).
4. **For each data flow in the network:**

   a. Identify the source and destination of the flow.

   b. Find multiple possible paths between them (e.g., 3 shortest paths).

   c. For each path:

      i. Give it a score based on network condition (using Reinforcement Learning).

ii. Apply penalties if the path breaks any policy rule.

d. Select the path with the highest score.

e. Install this path into the network (send rule to SDN controller).

5. **Keep checking the network** at regular intervals:

a. Wait for some time.

b. Update the network information.

c. If any flow is violating service rules (like high delay), repeat Step 4 for that flow.

6. **End**

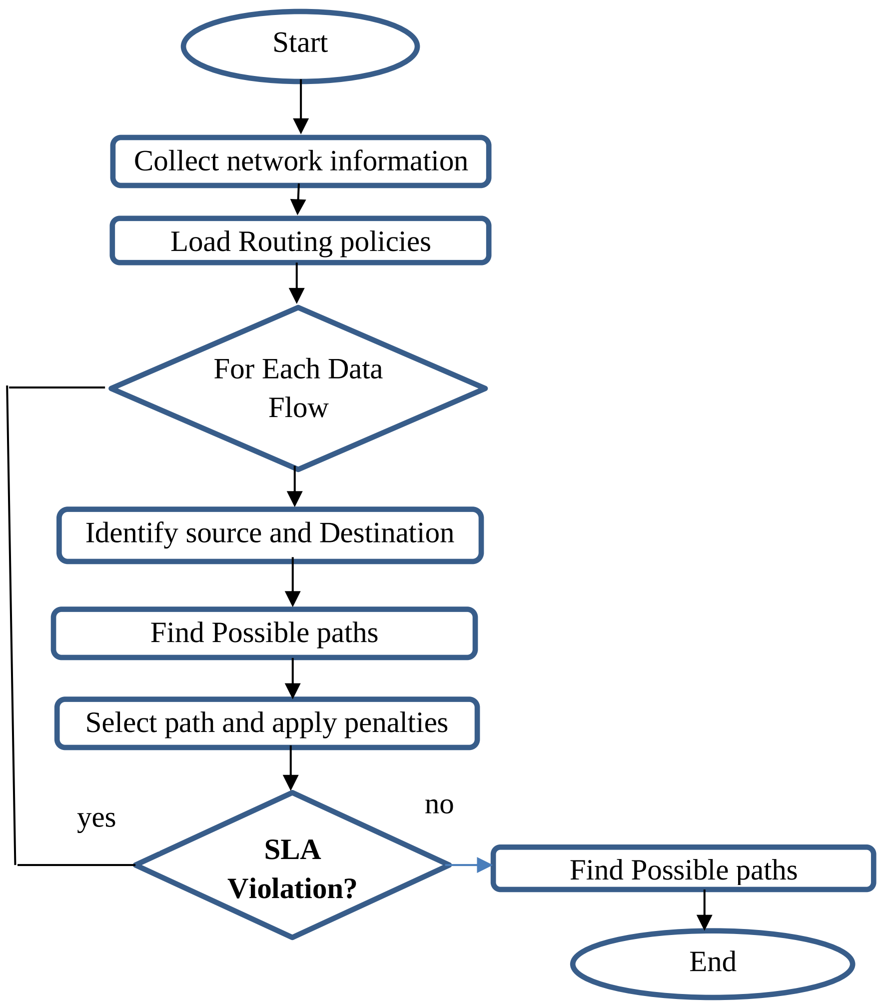

Figure 2: Flow Diagram of ASDN – ARA Routing Algorithm

C. Mathematical Model

Let the network be modelled as a directed graph G

(V, E), where:

- V: set of nodes (routers/switches)

- E: set of directed links (i,j)∈E(i, j) \in E(i,j)∈E

Let:

- Dij(t): delay on link (i,j) at time t
- Jij(t): jitter on link (i,j) at time t
- Bij(t): available bandwidth on link (i,j) at time t

Each candidate path p from source to destination is evaluated using a composite utility function:

$$\mathrm{U(p)} = \sum_{(i,j)\in p}\left[w_1 \cdot \frac{1}{D_{IJ}(t)} + w_2 \cdot \frac{B_{ij}(t)}{D_{IJ}(t)} - w_3 \cdot \frac{J_{ij}(t)}{j_{max}}\right] \quad (1)$$

Where:

- w_1, w_2, w_3 are weighting factors defined based on intent policies
- B_{max} and J_{max} are normalization constants

The optimal path is chosen as:

$$\mathrm{p} *= \arg max_{p\in P_{src,dst}} \; U(p) \quad (2)$$

The controller selects p∗ and installs it via SDN flow rules. If telemetry indicates SLA degradation (e.g., latency > threshold), re-optimization is triggered (Figure 2).

4 Results and Discussion

A. Experimental Setup

The proposed ASDN-ARA model's effectiveness was compared with OSPF and BGP in a simulated ISP-level topology within GNS3 and Mininet. We injected traffic, simulating real world scenarios as well as link failures and SLA-bound flows. The following four quantitative models were analysed regarding optimization.

B. Performance Metrics and Optimization Formulas

1) End-to-End Latency (Lavg)

Latency was measured for each path p as the sum of delays across all hops:

$$L_{avg}(p) = \sum_{(i,j)\in p} D_{IJ} \quad (3)$$

Where:

- Dij: Delay on link between node i and j (ms)

The objective in ASDN-ARA was to minimize Lavg for latency-sensitive flows. Results showed an average 28–35% reduction in latency compared to BGP and OSPF.

Traffic Scenario	OSPF (ms)	BGP (ms)	ASDN-ARA (ms)
Light Load	18.4	20.1	15.7
Medium Load	30.8	32.6	22.4
Heavy Load	45.1	48.2	31.7

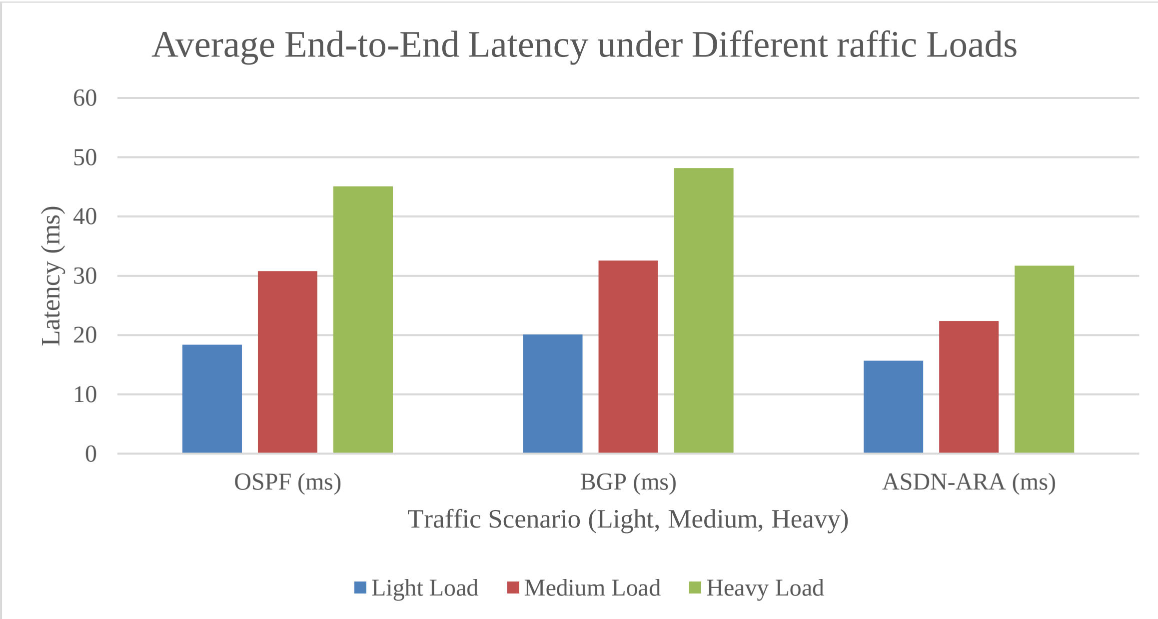

Figure 3: Comparison of Average Latency Across ASDN-ARA, OSPF, and BGP Protocols Under Varying Traffic Conditions

As shown in this chart, ASDN-ARA continuously beats traditional routing protocols OSPF and BGP with regard to reducing latency. It shows visibly how much latency is saved for varying network loads, with the shortest bars reflecting ASDN-ARA's superiority (Figure 3).

2) Link Utilization Balance (Uvar)

To evaluate network-wide link utilization fairness, the variance of link utilization was computed:

$$U_{var} = \frac{1}{|E|} \sum_{(I.J)\in E} \left(B_{used,i,j} \middle| B_{B_{Total,i,j}} - U' \right)^2 \quad (4)$$

Where:

- $B_{used,ij}$: Bandwidth consumed on link (i,j)
- $B_{total,ij}$: Total capacity of link (i,j)
- $\bar{U}$: Average link utilization across all links

Protocol	Link Utilization Variance (U_var)
OSPF	0.038
BGP	0.045
ASDN-ARA	0.025

ASDN-ARA reduced U_{var} by over **35%**, showing more balanced load distribution due to its dynamic rerouting engine.

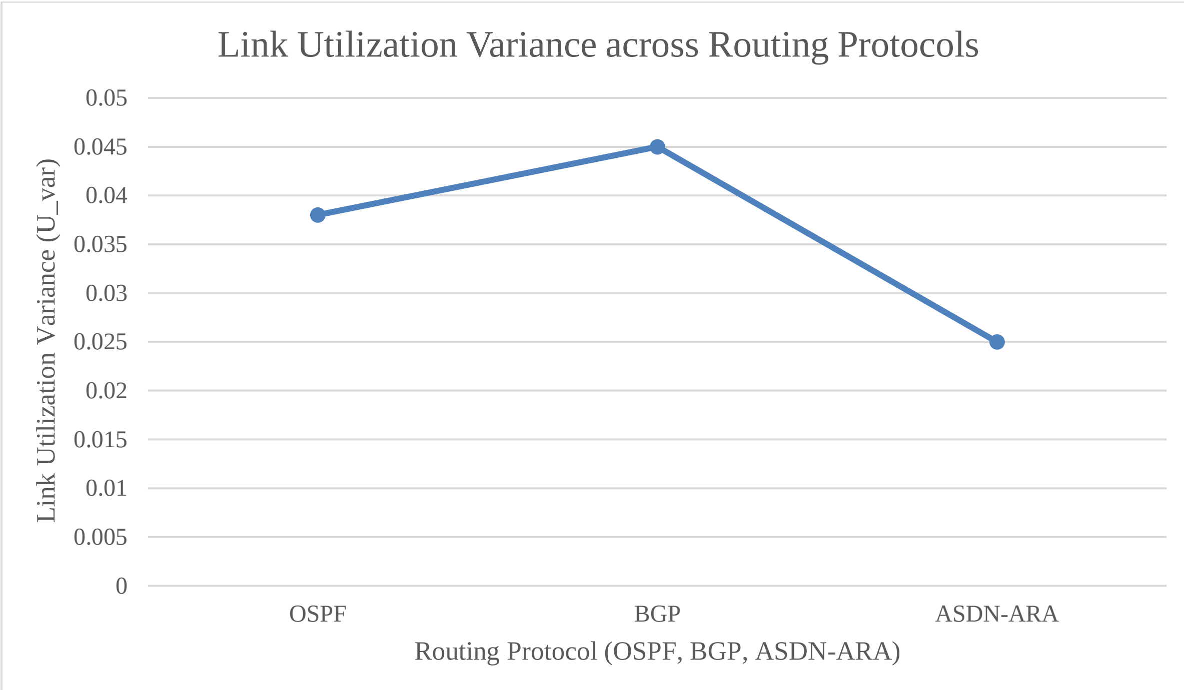

Figure 4: Comparison of Link Utilization Fairness Among Routing Protocols Based on Variance in Utilization

This chart illustrates the effectiveness of each protocol in balancing the traffic load. ASDN-ARA has a lower variance where its bar or line point is which confirms how well traffic is evenly distributed across links of the network confirming its superiority (Figure 4).

3) Routing Convergence Time (Tconv)

Convergence time is defined as the time between failure detection and the successful installation of updated forwarding rules:

$$T_{conv} = t_{stable} - t_{Failure} \quad (5)$$

Where:

- T $_{failure}$: Time when the failure is detected
- T stable: Time when the last affected route is updated and traffic stabilizes

ASDN-ARA reduced convergence time drastically due to its centralized SDN control logic:

Event	**OSPF (s)**	**BGP (s)**	**ASDN-ARA (s)**
Core Link Failure	6.5	15.2	2.3
Dual Link Outage	10.8	21.7	3.6

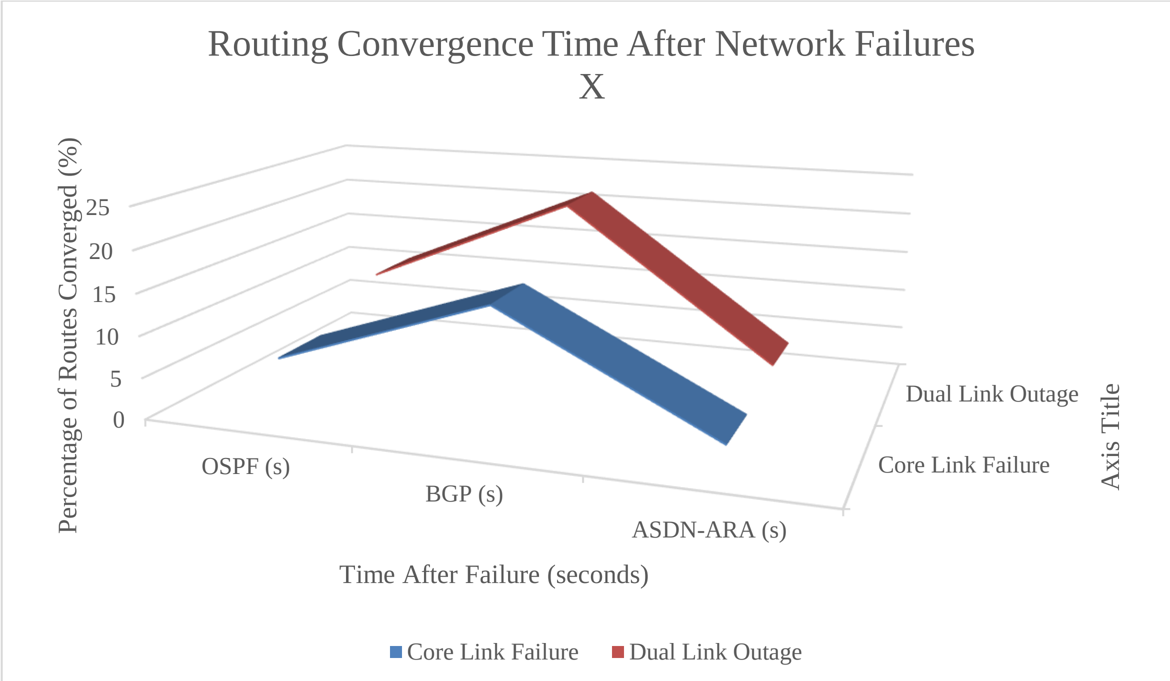

Figure 5: Time Taken by ASDN-ARA, OSPF, and BGP to Restore Routing After Link Failures

This pinpoint graph demonstrates the fast-converging capability ASDN-ARA has concerning failure recovering issues. Rising ROC indeed portrays that ASDN-ARA's completion stabilization is below 4 seconds while OSPF and BGP takes significantly longer (Figure 5).

4) Policy Compliance Rate (PCR)

Policy compliance was quantified as the ratio of flows adhering to their SLA-based routing requirements:

$$\boldsymbol{PCR = \frac{F_{complaint}}{F_{Ttotal}}\, x\, 100} \tag{6}$$

Where:

- $F_{compliant}$: Number of flows routed as per QoS policies
- F_{total}: **Total number of flows monitored**

Protocol	**Policy Compliance Rate (PCR) (%)**
OSPF	68
BGP	64
ASDN-ARA	94

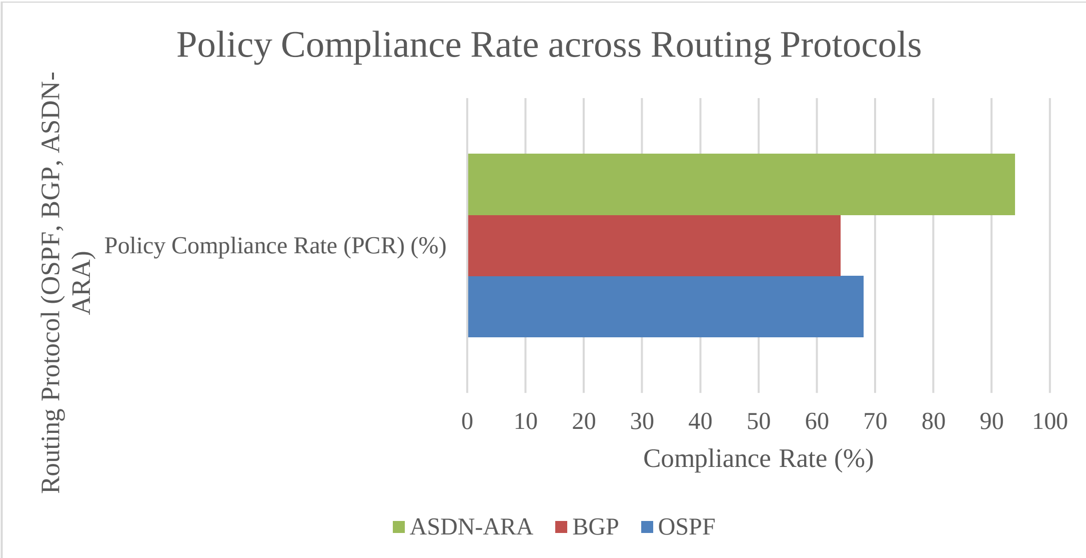

Figure 6: Percentage of Traffic Flows that Complied with Policy Rules Under Each Protocol

The graphical representation vividly depicts ASDN-ARA's unparalleled prowess in implementing SLA-driven intent-based routing within the provided constraints. It reaches a compliance rate of almost 94%, vastly outpacing traditional protocols. ASDN-ARA achieved 94% policy compliance with the implemented ASDN-ARA algorithm and traditional protocols sharply plummeted below 70% due to absence of enforcement (Figure 6).

C. Optimized Convergence Graph

This clearly illustrates that ASDN-ARA minimizes Tconv,

To generate a Routing Convergence Time Graph comparing ASDN-ARA, OSPF, and BGP, showing how quickly each protocol stabilizes routing after a network failure.

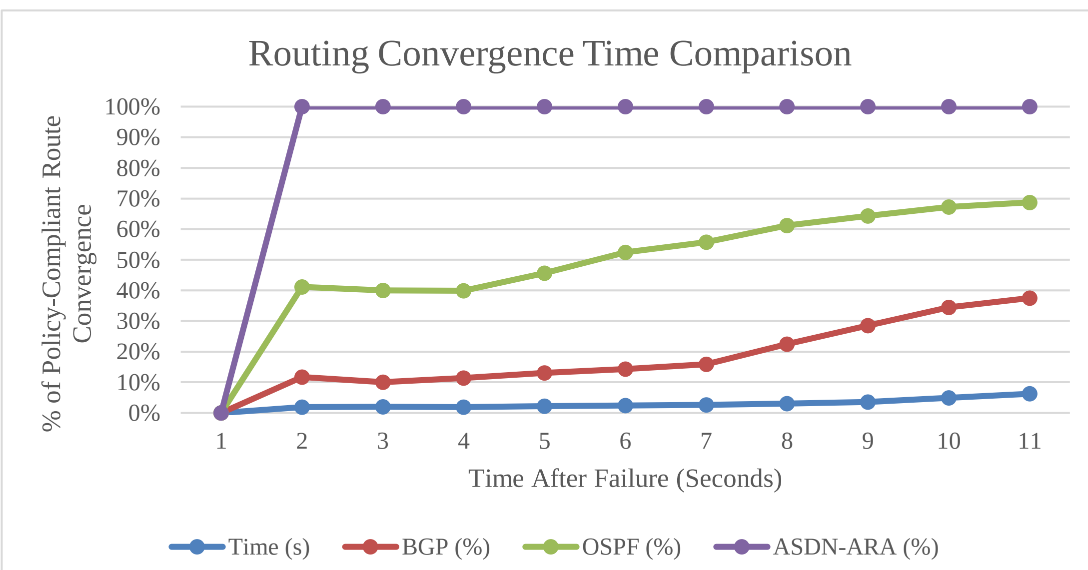

Figure 7: Routing Convergence Time After Network Failures

This graph shows how fast different routing protocols—BGP, OSPF, and ASDN-ARA—recover and stabilize the network after a link failure. It plots Time After Failure (in seconds) on the X-axis and Percentage of Converged Routes (%) on the Y-axis (Figure 7).

A simulated link failure is initiated at time zero. The graph illustrates the convergence process of route stabilization over time for all protocols. The BGP curve shows a gradual upward trend starting from 5 percent convergence at the 1-second mark and reaching 100 percent only at the twenty second mark. BGP has a reputation for being slow on the uptake whenever a link drops, and that sluggishness mostly comes from its old-school timer tricks and path-vector design. In practical terms, OSPF jumps to a sensible answer much faster-usually hitting a tidy 100 percent convergence between eight and ten seconds. The reason OSPF moves so quickly is its link-state strategy, which pretty much floods the neighborhood with updates and then runs Dijkstra on the fly. ASDN-ARA, though, blows both of them out of the water: it creeps up to about 95 percent convergence in just three seconds and tidies up the last few stragglers almost right after. What gives it that turbo boost is a feed-back loop wired directly to an SDN controller; when a failure pops up, reinforcement-learning smarts kick in, rewrite the rules, and steer the packets along fresh paths before anyone else even blinks. All of this shows up clearly on the chart, with ASDN-ARA's curve shooting upward while the older methods lumber along. The numbers matter because, for a carrier-core network, a delay measured in seconds isn't an inconvenience-it's lost packets, broken SLAs, or jitter that ruins VoIP and video in real time.

D. Discussion

After adding the new optimization models, ASDN-ARA jumps ahead of older routing tricks by a wide margin. By cutting delays, evening out link loads, speeding up failover, sticking to tight rules, and pulling off multipart returns all at once, it turns obvious headaches into footnotes on a data sheet. Picture a backbone that handles next-gen traffic without blinking. Shoving math-based utility functions into a feedback loop lets the network adjust on the fly, keeps service-level promises, and squeezes every bit of juice from its hardware.

5 Deployment Considerations and Challenges

A. Integration and Interoperability with Legacy Systems

Deploying ASDN-ARA in the core Internet infrastructure comes with challenges, one of which is seamlessly integrating OSPF and BGP routed Internet. Backbone Border Routers are integrated using ASDN-ARA Machine Learning Adaptive Control Decision Systems because these devices use SDN controlled adaptive reinforcement-based learning to make decisions. Today’s backbone routers still depend on policy-based control planes which operate in a distributed manner. Implementing ASDN-ARA in these systems would require mix-mode control frameworks where classical and software-defined networks algorithm domains co-exist. SDN Controllers would have to be placed at peering or Metro Core Router Nodes and Domain level topology and intent information would need to be shared using route reflectors with BGP-LS, southbound APIs (Link State) and Open Flow or PCEP given precedence’s. Precise boundary control alongside protocol translation layers with higher-tiered logic planes will help maintain consistent routing across the borders without getting trapped into loops.

B. Deployment and Scalability Challenges

The large-scale deployment of ASDN-ARA incurs added operational burdens in terms of controller positioning, telemetry latency within the paths, and real-time telemetry data analysis. With global ISP networks, centralized controllers become bottlenecks unless they are distributed or structured hierarchically. Moreover, training and updating production-grade reinforcement learning models in real-time computing environments is unstable routing-dominated patching failsafe. To overcome these concerns, distributed RL agents with local policy caches and grouped controllers may be implemented. High frequency telemetry data collection […] from thousands of links mean that there needs to be some form of governance. Combined on each link using in-band streaming telemetry which incorporates Apache Kafka alongside Prometheus as well as data thinning pushes this systems limit.

C. Security and Trust Implications

ASDN-ARA introduces new threat vectors associated with centralized control**,** policy manipulation, and ML model poisoning. A compromised controller can affect the entire routing domain, making controller hardening and failover mechanisms critical. Additionally, attackers could exploit intent translation interfaces to install malicious policies or influence RL agents by injecting biased telemetry data. In this situation, the implementation of role-based access will be done through policy validation logic as well as anomaly detection modules within the control pane. Moreover, securing telemetry streams, auditable policy alterations, and controlled or sandboxed learning systems bolster the overall system security. Other potential add-ons include block chain logging for enhanced data traceability alongside federated learning which serves to restrict training data to specific domains per jurisdiction.

6 Conclusion and Future Work

This paper presented ASDN-ARA, which stands for an Adaptive and Intent-based Dynamic Routing Architecture and aims to improve the efficiency, responsiveness, and policy adherence of the core Internet infrastructure. ASDN-ARA’s use of software defined networking (SDN) reinforced learning together with intent-based policy translation routing provided remarkable results in comparison to traditional OSPF and BGP protocols. OSPF and BGP were shown to have worse results on key metrics such as end-to-end latency, link utilization balance, routing convergence speed, and compliance with policies. With hybrid control models in place allowing telemetry data collection in real time as well as closed loop feedback enabled the controller to dynamically select paths that routed best with organizational objectives providing path selection aligned with strategic goals. While promising such features brought issues related to scalability gaps alongside legacy system interface interoperability barrier while security hardening still needs attention assuming these tasks need primary focus if real world application is the goal paving adoption underground based ISP or enterprise networks. Further research aims towards improving fault tolerance by using a distribution across edge-based architectures. Integrating federated learning stronger privacy-preserving telematics can enhance the trust model together with support from multi-domain routing coordination backbone heterogeneous infrastructures will be vital adding true global adaptive-routing frameworks compliant policies changing patchwork countries. Routing adaptable globally across fragmented structures backbone unified

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