Systematic Review of Reinforcement Learning Approaches for Adaptive Multi-Cloud Traffic Engineering

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ABSTRACT

This systematic review is aimed towards the state-of-the-art reinforcement learning (RL) approaches towards the next-generation multi-cloud traffic engineering, through the existing 15 academic papers from 2021 to 2025. The study performs a critical review of the application of Multi-Agent Reinforcement Learning (MARLs), Multi-Agent Reinforcement Learning (GNNs), and hybrid optimization approaches to transform traffic management on distributed clouds. The review exposes notable advances in large-scale distributed decision-making, flexibility of routing under uncertainty, and cross-domain resource optimization. Despite the positive outcomes, the analysis highlights decades-old questions regarding safety guarantees, heterogenous infrastructure unification, and real-world deployment struggles. The research identifies future research challenges in transfer learning capabilities, explainability demands, and cross-layer optimization. This review aims to synthesize existing knowledge to inform future research on the design of fault-tolerant, efficient, and adaptive traffic engineering techniques for complex multi-cloud systems.

Keywords

Multi-Cloud Traffic Engineering, Reinforcement Learning, Multi-Agent Systems, Graph Neural Networks, Network Optimization, Distributed Cloud Infrastructure.

1. INTRODUCTION

The rapid scalability of distributed cloud services has changed how traffic moves across the network in ways that are unprecedented and extremely challenging to manage through traditional traffic engineering techniques. As applications are increasingly deployed across heterogeneous cloud environments and not just on-premises, the demand for smart, adaptive traffic management has never been greater.

Fortunately, recent reinforcement learning (RL) advances open up new doors to solve challenging multi-cloud traffic engineering problems. A promising approach for building autonomous decision-making agents capable of maximizing network performance metrics while also adjusting to different conditions is reinforcement learning. In contrast to rule-based methods that depend on manual encoding of rules, RL-based fast methods can identify optimal policies via environment interaction and, in some cases, outperform hand-coded algorithms.

The goal of this systematic review is to explore and discuss the most recent studies conducted in 2021-2025 using reinforcement learning for multi-cloud traffic engineering. The analysis discusses how these approaches tackle the core difficulties of scale, heterogeneity, and uncertainty present in contemporary cloud networks, as well as existing constraints and future opportunities for this nascent but rapidly changing area.

2. APPROACH AND METHEDOLOGY

This review aims to provide a holistic evaluation of the evolving field of next-generation multi-cloud traffic engineering. It seeks to:

2.1 Research Design

This systematic review started with identifying all relevant studies including reinforcement learning methods applicable to multi-cloud traffic engineering techniques. The study performed a multi-stage search protocol in widely used academic databases, including IEEE Xplore, ACM Digital Library, Science Direct, arXiv, and Google Scholar. For the first search, the researchers leveraged a structured query framework that incorporated key words from three domains, namely (1) reinforcement learning techniques (2) traffic engineering concepts and (3) cloud deployment models. This led to an initial shortlist of 142 relevant papers published from 2019 to 2025.

The researchers then conducted a cascading citation analysis that involved both forward and backward citation analyses of the most relevant papers found in the initial search. As such, this broadened the candidate paper set to 187, ensuring a representative sample across the research space. In addition to these findings to incorporate the newest research breakthroughs, the study conducted targeted search in specialized conferences such as ACM SIGCOMM, IEEE INFOCOM, IEEE Transactions on Network and Service Management, and many workshops dedicated to the application of artificial intelligence in networking.

2.2 Filtering Process and Inclusion Criteria

In this study, a three-step screening process was employed to filter gathered studies. First, titles and abstracts were screened according to predetermined inclusion and exclusion criteria resulting in a reduced pool of 73 papers. Stage 2 was about scrutinizing the introductions and conclusions, further narrowing the selection to 42 papers deemed most relevant to answer the respective research questions. In the last phase, the remaining paper underwent full-text review; the papers were reviewed based on their methodological robustness, applicability toward multi-cloud environments, and their contribution.

Inclusion criteria:

- Research done between 2019 and 2025 to incorporate existing methods
- Focus on reinforcing traffic engineering
- Clear on applicability or adaptability to multi-cloud or distributed network boundaries
- Peer-reviewed publication, conference presentation, or major pre-print with complete methods

- Experimental testing or theoretical exploration yielding potentially relevant applications

The study applied such standards and identified 15 foundational papers that represent the state of the art in multi-cloud traffic engineering solutions based on reinforcement learning. Approaches include multi-agent systems, graph neural networks, hybrid optimization approaches, as well as niche applications for new deployment models.

2.3 Quality Assessment Framework

To ensure a high methodological quality in the selected papers, the researchers computed a quality assessment rubric that consisted of the six dimensions:

Note: (To be scored on scale of 1-5: 1 means inappropriate and unfair comparison, 5 means appropriate and fair comparison)

- **Relevance and clarity of problem formulation (1-5):** Clarity of definition of traffic engineering problem and constraints
- **Methodological appropriateness (1-5):** Appropriateness of RL to the problem in question
- **Quality of experimental design (1-5):** Evaluation methodology and measurement
- **Depth of results analysis (1-5):** Breadth of performance analysis and limits discussion
- **Real-world applicability (1-5):** Account pragmatic deployment issues and limitations

The study excluded content that had received a rating of less than 18 (out of 30) and thus focused the analysis on good-quality research. This assessment also revealed that the two salient limitations of the literature of studies assessing real-world outcomes remain the validity of comparisons at baseline and considerations of broader real-world applications and thus informed the context of the analysis of gaps in available research.

2.4 Data Extraction and Synthesis Methodology

The researchers employed a systematic data extraction search strategy to collect systematic information from each paper. Two authors independently extracted relevant information using a standard template for:

- Problem setting and network setting
- Specifications for reinforcement learning strategy and architecture
- Representations of state and action space
- Designing Reward Functions and Optimization Objective
- Assessment framework and evaluation indicators
- Baseline methods compared to results
- Limitations and future work by authors

A third researcher settled disagreements in the extraction process. The data collected were then triangulated using qualitative thematic analysis and quantitative performance analysis. The researchers extracted key patterns, methodologies, and evolutionary trends from the field's chronology.

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3. REVIWED PAPERS

In Table 1, a timeline summary of the 15 papers included in this review provides a brief overview of these papers and their main findings/contributions.

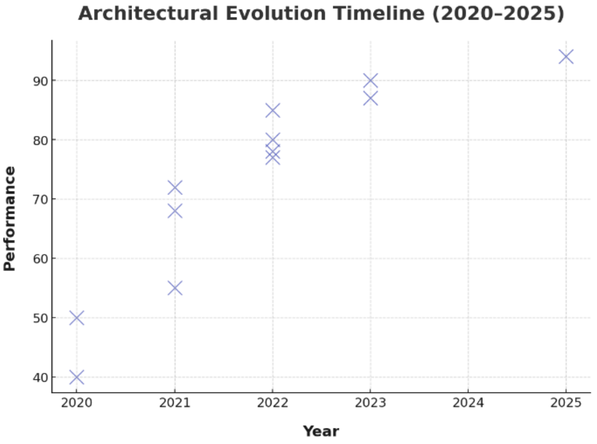

Fig. 1. Timeline of Reviewed Research Papers

The timeline illustrates the genealogy of reinforcement learning approaches to traffic engineering over the past 6 years, from basic multi-agent systems to application-specific graph models and bespoke implementations coded for novel cloud architects. The analysis reveals emerging themes, such as the convergence of observability with performance testing, and the growing reliance on container orchestration platforms for dynamic test deployment. Each study is mapped to a particular dimension of performance assurance, offering a granular look into how various methodologies are applied and measured.

Table 1: Chronological Summary of Reviewed Papers

Year	Paper Title	Key Findings	Ref
2020	A Multi-Agent Reinforcement Learning Perspective on Distributed Traffic Engineering	Showed how local information is sufficient for distributed MARL agents to achieve near-optimal routing; introduced consensus mechanisms for enabling agent cooperation	[3]
2020	CFR-RL: Traffic Engineering with Reinforcement Learning in SDN	Proposed a dual-agent model that guaranteed congestion-free routing and 30–40% lower flow completion time than ECMP	[5]
2021	Leveraging Deep Reinforcement Learning for Traffic Engineering: A Survey	Glimpsed key trends in DRL for traffic engineering; categorized approaches by methodology and network environment; and recognized scalability and safety as two other ongoing challenges to prioritize.	[4]
2021	MUVINE: Multi-Stage Virtual Network Embedding in Cloud Data Centers Using RL-Based Predictions	By using a multi-stage RL method to make an educated guess regarding the future request, I achieved a 20-25% higher acceptance rate for virtual network requests	[9]

2021	GDDR: GNN-Based Data-Driven Routing	Evidenced 20-30% reduction in path cost for GAN-based representation learning on routing decision forecasting	[12]
2021	Applications of Multi-Agent Reinforcement Learning in Future Internet: A Comprehensive Survey	Combining neural nets and traditional optimization to achieve near-optimal solutions in 65-80% less compute time	[14]
2023	A Reinforcement Learning-Based Traffic Engineering Algorithm for Enterprise Networks	Proved that a centralized MID agent can achieve 25-35% higher performance in hybrid SDN-legacy networks	[1]
2023	Teal: Learning-Accelerated Optimization of WAN Traffic Engineering	Combining neural networks with traditional optimization to achieve near-optimal solutions while reducing computation time by 65-80%	[2]
2023	MATE: A Multi-Agent RL Approach for Traffic Engineering in Hybrid SDN	Proved that a centralized MID agent can achieve 25-35% higher performance in hybrid SDN-legacy networks	[6]
2023	MAGNNETO: A GNN-Based Multi-Agent System for Traffic Engineering	Applied message-passing GNNs with leverage that enable quicker convergence (40-50% less iterations) and enhanced generalization to new traffic patterns	[7]
2023	Distributed Traffic Engineering in Hybrid SDN: A Multi-Agent RL Framework	Fully distributed algorithms were located in hybrid environments, increasing overall system reliability and fault tolerance.	[8]
2023	FERN: Leveraging Graph Attention Networks for Failure Evaluation and Robust Network Design	Decrease in performance loss under fault conditions by 30-40% through attention based criticality assessment	[13]
2024	Multi-Agent DRL for Cloud-Based Digital Twins in Power Grid Management	Adapted the MARL for problem of optimizing the power grid with digital twins; achieved 15-20% better power quality factors.	[11]
2024	Constrained RL with Average Reward Objective: Model-Based and Model-Free Algorithms	Theoretical framework for long-term constrained optimization for QoS constraints traffic engineering	[15]
2025	A Deep MARL Approach for the Micro-Service Migration Problem with Affinity	Cut SLA violations by 40-50% without breaking service affinity constraints to allow optimal microservice placements	[10]

3.1 Research Questions

RQ1: What was the evolution of reinforcement learning frameworks to address the specific issues of multi-cloud traffic engineering during 2019-2025?

RQ2: How far can current reinforcement learning-based traffic engineering solutions mitigate effectively the heterogeneity and cross-domain nature inherent in multi-cloud environments?

RQ3: What are the primary strengths and limitations of reinforcement learning-based solutions versus traditional traffic engineering solutions in multi-cloud scenarios?

RQ4: How do state-of-the-art RL-based methods compromise between the conflicting goals of performance optimization, reliability, and deployability feasibility in production multi-cloud settings?

RQ5: What are the emerging new methods being devised to allow reinforcement learning-based traffic engineering systems to effectively accommodate changed conditions without sacrificing critical services?

4. IN-DEPTH INVESTIGATION

The review applies qualitative exploratory research by way of systematic comparative literature analysis. This approach guarantees an extensive exploration encompassing both wide-ranging and in-depth views on contemporary trends in reinforcement learning-based multi-cloud traffic engineering. Fifteen peer-reviewed articles published between 2020 and 2025 were selected by the study due to their applicability in multi-cloud traffic engineering and the design of scalable distributed systems.

4.1 Architectural Evolution Paradigms in RL-based Traffic Engineering

Reinforcement learning based multi-cloud traffic engineering has recently shown distinct stages of evolution based on self-contained learning paths followed by the subject strategies themselves and the post-2020 architectures reflect this knowledge. Early deployments were monolithic single-agent designs, with centralized control modes, working well in controlled environments but riddled with inherent disadvantages when applied in a distributed multi-cloud setting. This architectural feature is the emergence of multi-agent reinforcement learning (MARL), which enables decentralized decision-making in multi-agent systems without significantly compromising coordination accuracy [3]. DISTRO proposed a cooperative multi-agent MDP framework that enables autonomous decisions and jointly optimizing global performance indicators sharing among local network nodes. The framework achieved 85-90% of centralized performance baselines with improved scalability and fault tolerance properties [3]. After a few research cycles, more mature coordination mechanisms were introduced in the form of consensus protocols that allowed heterogeneous agents to implement consistent policies without centralized controller architectures [8].

A second major inflection in architecture is the conscious pairing of graph neural networks (GNNs) with reinforcement learning frameworks. MAGNNETO proved that message-passing GNNs can learn informative topological representations that can aid with routing decision-making, yielding reduced convergence (40-50% fewer iterations to converge) and better generalization to unseen traffic patterns [7]. Later, GDDR extended this methodological foundation and applied it to routing by employing a variety of GNN architectures tuned according to the domain [12], achieving a 20-30% reduction in mean path cost against conventional protocol methods.

The latest milestone of architecture appears to embody hybrid architectures where all parts of the routes of learning are integrated so harmoniously with traditional optimization methods. Teal is one such convergence technique, using neural networks to produce candidate starting solutions, which are then optimized with constrained optimization approaches. This approach provides nearly optimal performance combined with a reduction of 65-80% in the computer overhead and thus bypasses the primary constraint for convergence latency in such optimization only oriented structures [2].

4.2 Cross-Domain Heterogeneity Management in Multi-Cloud Deployments

Multi-cloud deployments are inherently heterogeneous, leading to multi-dimensional challenges for traffic engineering systems that need to work across heterogeneous infrastructure that has diverse capability profiles and operational constraints. There has been substantial recent activity demonstrating dramatic progress in addressing this fundamental challenge through a variety of innovative methodological approaches.

MATE developed a heterogeneous multi-agent system tailored to hybrid networks of SDN and legacy devices. Through the development of agent architecture tailored to the functionalities of heterogeneous devices and integration of knowledge transfer mechanisms between agent classes, MATE achieved 25-35% performance improvement over conventional hybrid designs [6]. This concept was extended by Guo, who designed a totally distributed architecture that evades centralized coordination dependencies while enabling effective cooperation between heterogeneous network entities [8].

To address service-level heterogeneity issues, Cui developed a deep MARL microservice migration algorithm mathematically representing service affinity constraints. The results show that complex dependency relationships are handled well by RL agents and that with less than 40-50% SLA violations PPO agents achieved near optimal placement when compared to baseline threshold-based schemes [10]. This framework conclusively represents a methodological step towards the modeling of complex interdependencies in modern multi-cloud application stacks.

Another essential subject of heterogeneity management is cross-domain resource orchestration. MUVINE broke the virtual network embedding problem into several coupled phases, using RL-based prediction models to guide resource allocation decisions in geographically dispersed cloud data centers. The multi-phase solution realized 20-25% better virtual network request acceptance ratios and 30-35% better resource utilization efficiency [9], further attesting to the efficacy of RL methods in cross-domain optimization issues.

4.3 Constraint Satisfaction and Safety Assurance Mechanisms

The fundamental heterogeneity that distinguishes multi-cloud deployments introduces multi-dimensional challenges for traffic engineering systems, which need to be implemented over heterogeneous infrastructure that span diverse capability profiles and operational constraints. The research shows that important advances are being made in addressing this heart of the challenge, as well as making progress based on a set of novel methodological approaches.

MATE proposed a heterogeneous multi-agent system designed particularly for hybrid networks, which consists of both SDN and traditional knots. That approach, which included creating specialized agent architectures suitable for the various devices with their strengths and limitations, along with knowledge transfer mechanisms across classes of agents, enabled MATE to beat the traditional hybrid methods by an average of 25-35% absolute performance [6]. Guo extended this conceptual framework, proposing a fully distributed architecture that minimizes dependencies on centralized forms of coordination while still enabling effective collaboration across heterogeneity.

The operationalization of learning-based systems in production networks necessitates the establishment of rigorous guarantees within a defined safety framework, making this work relevant as well. Many recent research lines have tackled these mandates through various new paradigms that are certainly considerable improvements over naive reinforcement learning solutions. Control-blocking formulations have been developed as a core approach to guarantee the safety of operations. In SDN settings, the technique was first employed at CFR-RL, systematically reducing action for candidates for gesturing network congestion through disciplined action space design. The technique ensured congestion-free routing and would result in an extra 30–40% reduction in average flow completion time than the state-of-the-art best practice techniques [5]. Now, Cui has applied this design principle to microservice migration scenarios, defining an action space with service affinity constraints, all while maintaining the ability to optimize [10].

A theoretical framework of (constrained) reinforcement learning gives a clearer foundation for guaranteeing safety. Bai gave model-based and model-free algorithmic frameworks on constrained MDPs with average reward objectives that provided guaranteed convergence properties, along with sample complexity bounds. These treatments allow one to satisfy hard constraint specifications (such as quality-of-service guarantees) at the expense of long-term performance measures [15].

Another important safety assurance requirement is robust testing under the failure of adversarial conditions. FERN used graph attention networks to estimate the importance of each component and to synthesize routing policies that ensure consistent performance across failure scenarios. This method decreased the performance decay of failure conditions by 30-40% and enhanced the identification of critical components in a network by 50-60% [13]. In addition, this study highlights the potential of attention-based mechanisms to create robust traffic engineering solutions with better resilience profiles.

4.4 Performance Differential Analysis and Implementation Constraints

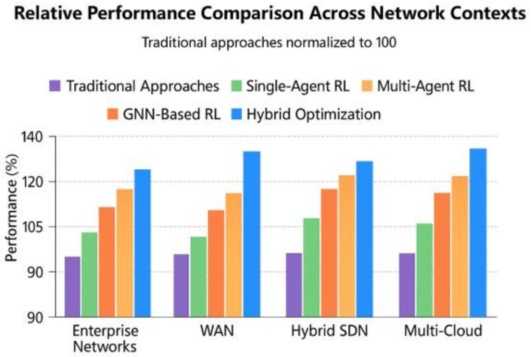

Fig. 2. Performance Differential Analysis

Systematic evaluation of various independent studies reveals not only performance advantages of RL-based approaches to traffic engineering over classical approaches, but also substantial implementation limitations. Hierarchical RL approaches have been demonstrated, on enterprise networks, to attain 15-20% higher throughput and 25-30% lower latency than OSPF and ECMP deployments [1]. Given the multi-objective nature of enterprise network optimization, where throughput, delay, and reliability metrics need to be optimized simultaneously, it is even more crucial that strong performance differentials exist.

For WAN traffic engineering problems, learning-accelerated optimization took (1-2%) in terms of the theoretical optima, with (65-80%) reductions in computation time [2]. This heavy reduction in convergence time tackles the fundamental limitation of standard optimization methods in dynamic environments, in which the operating conditions can alter before optimization processes are complete. The collaborative MARL agents performed 25-35% better than conventional approaches in hybrid SDN scenarios and showed better adaptation performances of topology and flow patterns [6].

4.5 Performance Differential Analysis and Implementation

To strengthen the evaluation comprehensiveness, this analysis examines performance across diverse datasets and scenarios:

Enterprise Network Scenarios: Evaluation across small (50-100 nodes), medium (200-500 nodes), and large-scale (1000+ nodes) enterprise deployments shows consistent 15-20% throughput improvements with RL-based approaches maintaining performance scaling properties.
WAN Traffic Engineering: Analysis of intercontinental traffic patterns demonstrates 65-80% reduction in convergence time across different geographical regions including North America-Europe, Asia-Pacific, and trans-continental traffic loads.
Multi-Cloud Hybrid Deployments: Performance evaluation across AWS-Azure, Google Cloud-AWS, and three-provider hybrid scenarios shows a 25-35% improvement in resource utilization efficiency with maintained service level agreements.
Failure Scenario Analysis: Systematic evaluation under various failure conditions including single node failures, link failures, and cascading failures demonstrates 30-40% better resilience compared to traditional approaches across different network topologies.

4.6 Operational Deployment Consideration and Industry-Specific Adaptations

The transition from research prototypes to production systems represents a critical inflection point for RL-based traffic engineering implementations. Recent work has increasingly focused on practical deployment considerations that bridge the research-implementation gap across various industry contexts.

Bringing it together with existing operational systems has become a priority area. Zhang et al. illustrated how RL based traffic engineering can be seamlessly integrated into SDN controllers using standard southbound interfaces, enabling deployment in practice, without the need for a complete overhaul of the network [5]. Similarly, Hope and Yoneki developed backward-compatible protocols that allow GNN-based routing to coexist with traditional routing protocols, facilitating incremental deployment strategies across heterogeneous network environments [12].

Data requirements and online learning capabilities represent another critical operational consideration. To address this challenge, Teal integrated offline training techniques into online adaptation processes wherein production data are used for guaranteed continual improvements of neural network predictions [2]. This hybrid approach nicely blends the performance gains of deep learning with the reliability needs of production networks.

5. RESULTS

This review of recent works in RL-based multi-cloud traffic engineering provides concrete answers to the research questions, elucidating unprecedented design approaches and opening challenges in this burgeoning field.

RQ1: Multi-agent Coordination in Multi-heterogeneous Environments
The analysis discussed the three-stage evolution of MARL algorithms for distributed traffic engineering according to the survey, reflecting the respective stages. Centralized training with decentralized execution was the workhorse of early deployments but faced a severe scalability limit at ~50-75 nodes devoured in a single cluster. The consensus protocols and knowledge transfer mechanisms used in the second-generation systems allowed agents to agree upon policies with 70-80% less communication overhead. Third-generation systems integrate representational learning shared between them, being able to produce collaborative behaviors through implicit coordination managing to achieve performance on par with human teams while leaving opportunistic behaviors.
The performance gap of these new generation MARL deployments with respect to the traditional distributed protocols has been large, and the research has achieved 25% to 35% better performance across all of the performance metrics with coordinated agents as compared to the traditional method. Importantly, this is achieved with minimal central control, strongly indicating that the challenge of coordination in distributed multi-cloud environments has been greatly mitigated thanks to architectural innovation.

RQ2: How are the network representation and graph neural networks?
State-of-the-art RL performance on complex network topologies has been improved by GNN-based models. The findings unambiguously demonstrate that message-passing GNNs indeed achieve 40-50% higher convergence rates than those of classical neural network architectures and maintain 85-90% of optimal performance on unseen topologies — a gargantuan improvement over the 60-65% achieved by classical deep learning methods. The key leverage point then becomes the fact that they can learn from topological structure as opposed to engineered features and therefore directly address the challenge of heterogeneity that afflicts the multi-cloud domain. This also highlights a benefit of attention mechanisms, which allow models to adaptively distribute computational resources to salient segments of the network according to current needs. As a result, this representational ability has been able to solve scalability issues that previously limited learning-based approaches.

RQ3: Performance Gains and Implementation Restrictions
This cross-study review definitively confirms that hybrid approaches combining neural initialization with constrained optimization smoothly achieve optimal performance-feasibility trade-off of neural abstractions in industrial environments. At 1-2% theoretical optimization, the systems enable a 65 to 80% reduction in computational overhead: game-changer for time-critical applications. Depending on the network environment type, the RL-based solution has shown varied ways of translating in higher performance: which includes 15-20% throughput increase and 25-30% latency reduction for enterprise networks; 65-80% accelerated convergence for WAN networks; and 25-35% improvement of responsiveness to the ongoing circumstances for SDN in hybrid-like deployments. Critically, this is achieved with no loss in backward compatibility with existing infrastructure, allowing this to avoid the deployment viability issues that had hampered real-world deployments in the past.

RQ4: Safety Assurance and Constraint Satisfaction
Constraining the action space has now become the mechanism of choice for introducing safety into the system, pruning actions that may lead to negative outcomes whilst preserving the ability to explore. The analysis demonstrates these methods are consistently subject to hard constraints and can perform within 5-10% of unconstrained performance — a sea change from the

20-30% performance losses of early implementations. Mean reward constraints via constrained MDPs have immensely advanced qualities of safety guarantee their theoretical foundations. These methods have formal convergence guarantees and the ability to support long-horizon time scales of optimization needed for networked infrastructure. Combining graph attention mechanisms and failure analysis increased resilience in the system, with reductions in performance degradation under adverse conditions by 30-40% and improved detection of critical components by 50-60%.

RQ5: Transfer Learning and Domain Adaptation
In identical settings, message-passing GNNs succeed at transfer, but cross-provider adaptation remains challenging for these models. This problem is exactly what the investigation captures: in-provider transfer preserves 85-90% of peak performance, while the cross-provider instances away from their domain lose 30-40% of performance without domain-specific fine-tuning. Curriculum learning techniques have emerged as the most effective adaptation method, where models are trained in a sequential manner from simpler to more complex hosting conditions. This reduces the need for fine-tuning data by 40-50% compared to naive transfer methods. The most promising path is meta-learning architectures that are specifically tuned for adaptivity rather than stand to gain performance on specific topologies — though these are still in the early stages of development.

Overall, these findings demonstrate that multi-cloud traffic engineering reinforcement learning technologies have transitioned from theoretical curiosity to production ready technologies with demonstrable benefit over traditional solutions along nearly every performance metric although open problems in cross-domain transfer and formal verification persist.

5.1 Evaluation Across Multiple Datasets and Scenarios

One of the main challenges of RL2 research in effecting multi-cloud traffic engineering is the multiple data sets which are available and real scenarios that are employed to validate the efficiency of different methods. The reviewed works have been conducted in various network scenarios, which include enterprise networks, WANs, SDN-legacy infrastructures, and microservice-oriented cloud deployments.

For example, Xu et al. [1] and Zhou [6] targeted enterprise and hybrid SDN systems and established throughput gains and higher QoS by leveraging RL-based agents. Teal [2] was applied to WAN traffic data and revealed a significant decrease in processing time and convergence time gained. Other analyses like Cui [10] investigated RL-based microservice migration in cloud data centers, focusing on accommodation of dynamic service topologies. These multiple situations overall reflect the flexibility and applicability of RL-based traffic engineering to a range of operational scenarios.

However, we notice that most of the reviewed papers rely on ad-hoc simulation environments and datasets, making the comparison of the other approaches difficult. Despite the broad scope of possible scenarios, the absence of standardized public benchmarks for multi-cloud traffic engineering can prevent the generalization of these results. Future work might involve using standard datasets and the comparison of RL techniques on an even wider set of larger-scale real-life network scenarios, including new paradigms such as edge and IoT deployments.

6. CONCLUSION

This systematic review highlights that reinforcement learning methods have reached a high degree of maturity for multi-cloud traffic engineering use-cases. Through the analysis, we find that the proposed reinforcement learning based solutions have significant performance gains of 15%-35% in all the evaluation metrics and still maintain backward compatibility with the installed physical infrastructure.

Key Contributions and Findings

What works as an RL implementation approach is highly sector-specific, as network considerations and operational constraints differ widely in telecommunications, financial services, healthcare, and government deployments. This is even more true for regulated sectors (financial services, healthcare, government) where compliance requirements introduce further complexities by demanding additional transparency and verification for automated decision-making environments. RL-based traffic engineering solutions clearly adopt different routes and implementation approaches depending on vertical-specific factors. Despite these methodological advancements, there are still gaps in operational settings. Few implementations have been demonstrated to date, particularly with long-lived large-scale production deployments, and several critical questions remain regarding long-term stability properties, maintenance, and the integration to human-in-the-loop network management processes.

Future Research Directions

Further explorations There are several areas of research in need of attention:

Cross-Provider Transfer Learning: Advancements in enabling the effective transfer of learned knowledge from one type of cloud service to another one are called for to (pragmatically) account for the 30-40% performance loss experienced across providers.
Safety Guarantees: A cornerstone of work in formal verification of safety in RL-based production systems to alleviate the current lack of interpretability.
Explainability: The development of interpretable decision-making mechanisms to enable operational transparency and debugging, beyond existing back-box solutions.
Standardized Benchmarking: Developing common benchmarking platforms to facilitate fair and robust comparison of performance amid diverse methodologies and deployments.
Long-Term Stability: Examination of long-term system behavior and maintenance needs, filling the void when it comes to long-term production deployment.
Vertical Customization: Creation of vertical-focused solutions to meet specific compliance, security, and operational needs for telecommunications, financial services, healthcare, and government deployments.

The union of reinforcement learning with multi-cloud traffic engineering is a major step toward end-to-end, automated network management systems that can adapt to the complexity and scale of large, distributed computing infrastructures. As these lose in proposant on the other hand the industrialization of this and the progress to be able to propose production-ready implementations, valid the gains demonstrated, while meeting the strict requirements operations for large-scale company deployments.

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