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Systematic Analysis of Quality-of-Service Optimization Strategies in Software-Defined Network Environments

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Abstract: Software-Defined Networking (SDN) heralds the future of networks with its programmability, centralized control, and flexibility that could easily surpass traditional networks in managing Quality-of-Service (QoS). This literature review, adhering to PRISMA 2020 guidelines, selects 62 studies from 1,142 initially found and published between 2016 and mid-2025, all of them peer-reviewed articles and obtained from four databases, IEEE Xplore, Scopus, Web of Science, and ScienceDirect. The review highlights six chief SDN-based research QoS enhancement methods: the machine, deep, and reinforcement learning methods; dynamic queuing and scheduling; controller positioning and load balancing; policy- or intent-based frameworks; telemetry-based closed-loop control; and combined SDN and legacy integration. The majority of the studies explore both data and control planes simultaneously. Improved performance parameters such as latency, throughput, jitter, and packet loss have been reported in the outcome, however, these results mostly come from small-scale testbeds, simulations, and synthetic workloads with very limited real-world deployment, security evaluation, energy assessment, or hardware-based validation. In any case, SDN is still considered to be an option for carrier-grade QoS optimization but its operational suitability is still not clear. Future research should focus on reproducible, realistic, and operationally grounded assessments to close the gap between theoretical promise and large-scale industrial implementation.

Keywords: Network telemetry; Quality-of-Service optimization; Reinforcement learning; Software-Defined Networking; Systematic literature review

Introduction

The modern era of networking is witnessing an unprecedented surge in traffic due to multiple converging factors: widespread 5G/6G deployments, massive proliferation of Internet-of-Things (IoT) devices, ultra-high-definition multimedia streaming, and the continuous industrial shift toward cyber-physical systems. While network demand growth is frequently cited as the cause of Quality-of-Service (QoS) challenges, it is increasingly evident that the primary cause lies in the rigidity of traditional network infrastructures. Legacy networks rely on static configurations, distributed decision-making mechanisms, and a lack of global visibility, which collectively prevent them from meeting stringent latency, jitter, or bandwidth requirements in dynamic and mission-critical applications (Karakus & Durresi, 2017; Mehraban & Yadav, 2025). Domains such as autonomous transportation, remote healthcare, and real-time industrial automation exemplify scenarios in which QoS failures can have severe consequences, ranging from operational inefficiencies to catastrophic safety risks (Ghafoor et al., 2018; Bi et al., 2019; Rezaee & Yaghmaee, 2020). Furthermore, the increasing adoption of multi-tenant cloud environments and network function virtualization (NFV) has introduced multiple stakeholders, each requiring enforceable service-level agreements over shared infrastructure, further complicating QoS management (Shahzadi et al., 2020; Wang et al., 2021).

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Software-Defined Networking (SDN) emerged as a transformative paradigm aimed at addressing the limitations of traditional networking architectures. By decoupling control from forwarding hardware and centralizing network intelligence in programmable controllers, SDN offers the potential for fine-grained traffic control, dynamic flow management, and real-time network-wide topology awareness (Kreutz et al., 2015; Al-Jawad et al., 2018). In principle, SDN allows network operators to orchestrate queue management, traffic engineering, and policy enforcement from a single logical point, which can dramatically enhance network adaptability. Early studies highlighted these capabilities as revolutionary, presenting SDN as a near-perfect solution to previously intractable QoS problems (Al-Jawad et al., 2018; Kamboj & Pal, 2021).

However, it is crucial to recognize that SDN is not a panacea. The very centralization that enables SDN to optimize traffic also introduces new bottlenecks, often referred to as the "SDN paradox." These include controller overload, increased latency in southbound signaling, and single points of failure, which together can compromise network reliability and scalability (Hock et al., 2013; Ali et al., 2019; Mehraban & Yadav, 2022). Additionally, as the number of switches and flow requests grows exponentially in large-scale deployments, classical SDN mechanisms struggle to maintain operational efficiency (Wang et al., 2017; Belgaum et al., 2020). Consequently, while SDN theoretically enables adaptive QoS management, real-world implementations often fall short of achieving production-grade performance, particularly in mission-critical or carrier-grade networks (Keshari et al., 2021; Karakus & Durresi, 2017).

To bridge these gaps, research has increasingly turned to intelligent, AI-driven approaches. Current efforts span multiple sophisticated techniques beyond mere internet acceleration. Deep reinforcement learning (DRL) is employed to learn latency-minimizing routes in real time (Bouzidi et al., 2019; Casas-Velasco et al., 2021; Chen et al., 2022; Kim et al., 2022), while predictive analytics anticipate network congestion before it occurs (Bouzidi et al., 2021; Li et al., 2021). In-band telemetry and machine learning classifiers facilitate per-flow quality-of-experience (QoE) estimation, providing granular visibility into network performance (Canovas et al., 2020; Yu et al., 2018). Furthermore, policy-based frameworks translate high-level objectives into enforceable routing rules, and resilient controller placement algorithms aim to mitigate single points of failure (Ali et al., 2024; Kamboj & Pal, 2021; Hock et al., 2013; Ali et al., 2019). Hybrid approaches that integrate SDN with legacy protocols or extend to optical and satellite networks further expand the applicability of SDN-based QoS strategies (Bi et al., 2019; Thyagaturu et al., 2016; Wu et al., 2021).

Despite these advances, a critical guidance gap persists. Practitioners lack comprehensive evidence on which AI-driven or policy-based techniques deliver measurable benefits under realistic, operational workloads. Many studies rely on small-scale simulations, synthetic traffic models, or isolated testbeds, which makes cross-comparison challenging and limits reproducibility (Abood et al., 2024; Alenazi & Ali, 2024). There remains limited clarity on operational overheads, scalability constraints, and resilience to network failures or security threats, highlighting the industry readiness gap. Consequently, SDN QoS optimization strategies are rarely ready for deployment in large-scale, mission-critical networks without further research and validation (Abd et al., 2025; Abdelghany et al., 2023).

The novelty of this research lies in its systematic, PRISMA-guided synthesis of QoS optimization strategies explicitly designed for SDN environments. Unlike studies focused on individual algorithms or narrow simulations, this work integrates architectural patterns, AI-based mechanisms, policy-driven frameworks, and hybrid approaches, critically evaluating trade-offs in latency, throughput, jitter, energy efficiency, scalability, and resilience. By consolidating evidence from the past decade of peer-reviewed literature, this study identifies persistent open challenges and highlights directions for future research to achieve operationally reliable QoS management. The study further distinguishes itself by not only cataloging strategies but also assessing their applicability under real-world conditions, thus providing actionable insights for both researchers and network architects.

In sum, this research is both timely and significant. As networks become increasingly complex, adaptive, and multi-tenant, traditional QoS mechanisms are no longer adequate. SDN, while promising, introduces its own challenges that require intelligent and carefully evaluated solutions. By systematically reviewing existing methods, identifying gaps, and highlighting practical limitations, this study equips the community with a roadmap for bridging the gap between theoretical promise and industrial reality. It informs decision-making for SDN deployments in critical domains, ensuring that QoS objectives—low latency, high throughput, fair bandwidth allocation, and reliable service—can be realistically achieved in the evolving landscape of modern networking (Abd et al., 2025; Abdelghany et al., 2023).

This study, therefore, addresses the core problem of QoS in modern networks not merely as a traffic issue, but as a structural and operational challenge, evaluates SDN as a flexible yet imperfect tool, and situates AI and policy-based approaches as key enablers of adaptive network performance. By doing so, it sets a clear foundation for evidence-based, large-scale SDN deployment, aligning research priorities with the practical needs of network operators and industrial stakeholders, while offering a comprehensive perspective on what works, what does not, and where efforts should be directed next.

Method

This study was conducted as a Systematic Literature Review (SLR), adhering rather strictly, study used, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines. The choice of a systematic approach was deliberate: given the sheer volume of publications on QoS in SDN and the rather fragmented nature of evaluation methodologies across the field, only a reproducible, transparent, and bias-minimised protocol would allow us to draw credible conclusions.

Research Questions

We formulated three primary research questions to guide the entire process:

RQ1: What are the main categories of Quality-of-Service optimization strategies proposed for Software-Defined Network environments in the recent literature?
RQ2: Which architectural components (controller placement, queue management, routing, monitoring, machine-learning integration, etc.) are most frequently targeted by these strategies?
RQ3: What are the reported performance gains, limitations, and open challenges associated with each category?

Search Strategy

A structured search was executed across four major academic databases that, in fact, dominate engineering and computer-science indexing: IEEE Xplore, Scopus, Web of Science (Core Collection), and ScienceDirect. No additional sources Google Scholar, arXiv, or institutional repositories were included so as to maintain the peer-reviewed quality threshold.
The search string combined four conceptual blocks using Boolean operators:

Table 1. Boolean Search String Used for Identifying QoS Optimisation Studies in SDN

Component	Search Terms
SDN Keywords	"Software-defined network*" OR "SDN" OR "software defined networking"
QoS / Performance Terms	"Quality of service" OR "QoS" OR "quality-of-service" OR "service level" OR "performance optimisation" OR "traffic engineering" OR "congestion control" OR "load balancing" OR "bandwidth allocation"
Mechanism / Strategy Terms	"strategy" OR "approach" OR "framework" OR "architecture" OR "algorithm" OR "mechanism" OR "scheme"
Functional / Technical Terms	"controller" OR "routing" OR "queue" OR "monitoring" OR "machine learning" OR "deep learning" OR "reinforcement learning" OR "intent-based" OR "policy-based"
Final Combined Query	(All four components combined with AND operators)

The Boolean string forming Table 1 has been developed to thoroughly look up literature on the topic of Quality-of-Service optimization in Software Defined Networking. The string has been deliberately prepared to comprise four logical groups of keywords referring to SDN terminology, performance metrics related to QoS, methods of optimization, and functional/AI methods. These logical groups are united by 'AND' operators, increasing the string's specificity, whereas each of the groups themselves is united by 'OR' operators, maximizing inclusiveness on the thematic level. This design enables searching literature covering SDN-related QoS problems either on classical traffic engineering methods or on more modern machine learning techniques. The developed Boolean string has been applied to thoroughly look up literature on scientific databases such as IEEE Xplose, Scopus, Web of Science, and Science Direct.

Filters used: Publication date: between January 2016 and June 2025 (to ensure inclusion of work after the maturation of OpenFlow); document type: restricted to journal articles, conference papers, and early access papers; language: restricted to English.

Inclusion and Exclusion Criteria

The criteria presented in Table 2 establish a rigorous, multi-layered filter designed to ensure the review's validity and focus. The inclusion criteria collectively mandate that studies must be technically substantive, empirically evaluated, and temporally relevant to contemporary SDN architectures.

Table 2. Inclusion and Exclusion Criteria for Study Selection

Inclusion Criteria	Exclusion Criteria
Publications explicitly addressing QoS optimization in SDN	SDN-only papers without QoS focus
Technical studies proposing or evaluating mechanisms, frameworks, or algorithms (AI and non-AI)	Conceptual surveys or opinion-based papers
Peer-reviewed journals, conferences, or early-access papers (English)	Books, theses, preprints, non-peer-reviewed sources
Published 2016–June 2025	Outside date range
Quantitative evaluation: simulation, emulation, testbeds, or analytical modelling	Purely qualitative or theoretical studies
Full-text accessible	Inaccessible full texts
Sufficient methodological detail for data extraction	Insufficiently reported data or unclear contributions

This prioritises actionable research over theoretical speculation. Conversely, the exclusion criteria systematically eliminate sources of bias and noise: non-peer-reviewed literature is excluded to uphold academic quality; studies lacking empirical data are removed to ground the synthesis in evidenced findings; and inaccessible texts are documented but excluded to maintain reproducibility. The most critical filter is arguably Criterion 5 (Evaluation Methodology), which ensures every included study provides *quantifiable evidence* of performance impact this transforms the review from a narrative of proposals into an analysis of demonstrated outcomes. The final 62 included studies thus represent a cohesive corpus of peer-validated, technically detailed, and empirically grounded research, enabling a robust synthesis that directly addresses the stated research questions.

Study Selection

The selection unfolded in clearly defined stages:

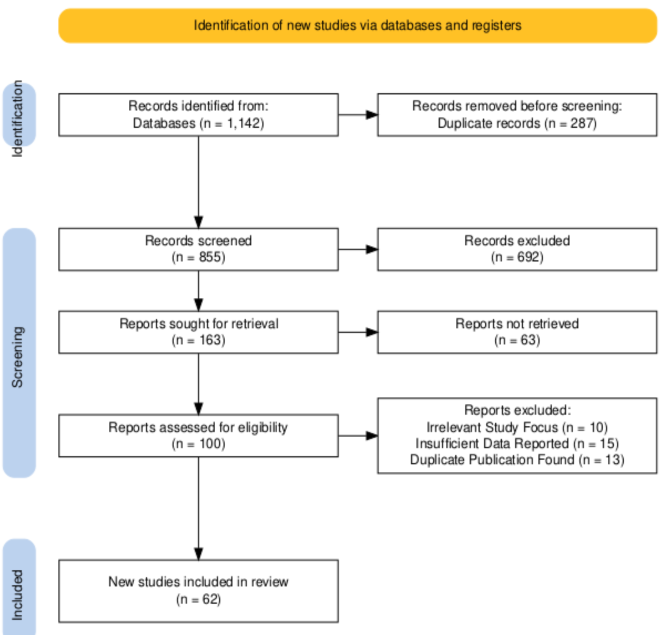

Figure 1. PRISMA Flow Diagram of Study Selection Process

The diagram clearly illustrates the critical three-phase funnel of systematic review methodology. *First*, in the Identification phase, comprehensive database searching yielded 1,142 records, from which 287 duplicates were automatically removed a substantial 25% reduction highlighting the necessity of rigorous deduplication before screening begins. This initial data hygiene is crucial for efficiency. *Second*, the Screening phase demonstrates rigorous filtering. From 855 screened records, 692 (81%) were excluded at title/abstract level, confirming the importance of well-defined, specific inclusion criteria to manage search yield. Subsequently, 163 full-text reports were sought, but 63 (39%) could not be retrieved a common practical hurdle often underreported in reviews that affects the comprehensiveness of the final synthesis. *Third*, the Inclusion phase reveals meticulous full-text appraisal. Of 100 assessed reports, 38 were excluded for substantive reasons: irrelevant focus (10), insufficient data (15), and duplication (13). This leaves 62 studies for synthesis. The exclusion of 13 additional duplicates at this late stage after initial deduplication is particularly noteworthy. It suggests that automated deduplication, while essential, cannot catch all duplicates, especially those with different metadata or in different repositories, necessitating manual vigilance throughout the process. The final inclusion of 62 studies from an initial pool of 1,142 represents a 5.4% inclusion rate, which is typical for a focused, well-scoped systematic review in a specialized field.

Data Extraction and Synthesis

The structured data extraction protocol was designed to systematically capture both quantitative and qualitative dimensions of the reviewed literature. The use of a piloted form and dual independent extraction ensured high reliability and minimized researcher bias. The captured categories facilitated a multi-faceted synthesis: bibliographic and technical data allowed for descriptive statistical mapping of research trends, while methodological details and performance outcomes enabled a comparative analysis of technical approaches and their claimed efficacy. Crucially, the inclusion of 'Critical Analysis' data ensured that the synthesis incorporated the authors' own reflections on limitations, providing a more nuanced and critical overview of the field's maturity. This comprehensive approach supported robust thematic clustering without attempting a statistically invalid meta-analysis due to the heterogeneity in metrics and experimental conditions.

Table 3. Data Extraction and Synthesis Protocol

Extraction Category	Specific Data Points Captured	Purpose/Rationale
Bibliographic Information	Publication Year, Venue (Journal/Conference), Title, Author Affiliation	To map the temporal and publication landscape, identifying trends, key research hubs, and geographic distribution.
Technical Focus	Primary Optimization Category (Routing, Resource Allocation, Queue Management, Controller Placement, Load Balancing, Policy-Based / Rule-Based, AI/ML-Based Approaches), Targeted SDN Architectural Layer (Control/Data/Application), Specific QoS Metric(s) Targeted	To categorize the technical scope and intent of each study, enabling thematic clustering across all six main approaches, not just AI-based methods.
Methodological Details	Evaluation Environment (e.g., Mininet, NS-3, ONOS, Custom Testbed), Network Scale (Number of Nodes, Flows), Algorithm/Mechanism Type (Neural Network Model, Reinforcement Learning, Policy-Based, Dynamic Queuing, Heuristic, Optimization Algorithm)	To assess the technical approach and the validity/generalizability of the experimental setup, capturing both AI-driven and traditional SDN-QoS methods.
Performance Outcomes	Key Performance Indicators (Latency, Throughput, PacketLoss, Jitter, Bandwidth Utilization), Claimed Improvement (%) Over Baseline, Statistical Significance (if provided)	To synthesize and compare the empirical efficacy of all QoS strategies, enabling fair comparison between AI-based and non-AI-based techniques.
Critical Analysis	Explicitly Stated Limitations, Potential Threats to Validity, Suggestions for Future Work, Scalability and Industrial Applicability	To provide a balanced view of the research, highlighting gaps, limitations, and areas requiring further investigation during synthesis.
Process	Two independent researchers performed extraction using a piloted Excel form. Disagreements resolved via consensus or third-author arbitration.	To ensure reliability, consistency, and minimize subjective bias in the data collection process, with all QoS approaches treated consistently.

Quality Assessment

Table 4. Study Quality Assessment Checklist

Quality Criterion	**Description & Scoring Guidance (0-2 points)**	Weight in Synthesis
Clarity of Research Objectives (Q1)	0: Unclear or absent. 1: Implied or partially stated. 2: Explicitly and precisely stated, with well-defined research questions or hypotheses.	High. Studies with well-defined objectives provide stronger, more interpretable evidence.
Adequacy of Methodology (Q2)	0: Methodology poorly described or inappropriate. 1: Methodology described but with minor omissions. 2: Comprehensive, reproducible methodology detailed.	High. Essential for assessing the validity and reliability of the experimental findings and their potential for replication.
Realism of Evaluation (Q3)	0: Purely theoretical or simplistic simulation (e.g., single topology, synthetic traffic). 1: Moderate realism (e.g., varied traffic, standard topologies). 2: High realism (e.g., testbed, real-world traces, large scale).	Medium. Influences the generalizability and practical relevance of the study's conclusions.
Discussion of Limitations (Q4)	0: No limitations discussed. 1: Limitations mentioned briefly or superficially. 2: Limitations discussed in depth, with implications for findings and future work.	Medium. Reflects scholarly rigor and provides context for interpreting the study's contributions and claims.

The quality assessment checklist, adapted from established systematic review guidelines, provided a structured mechanism to evaluate the methodological rigor and reporting transparency of each included study.

By scoring against four key criteria clarity of objectives, methodological adequacy, evaluation realism, and limitation disclosure the assessment moved beyond a simple binary inclusion to a nuanced grading of evidence strength. This process revealed a spectrum of quality within the field, helping to contextualize individual study findings. For instance, a high-scoring study conducted on a physical testbed received greater consideration in discussions of deployability than a low-scoring proof-of-concept using a simplistic simulation. Importantly, the scores were not exclusionary but instrumental in the synthesis phase, allowing for a more critical and weighted interpretation of the collective evidence, thereby enhancing the robustness and credibility of the review's overall conclusions.

Results and Discussion

A total of 62 primary studies published between 2013 and 2025 were included in this systematic review. The selected works cover a broad spectrum of QoS optimization strategies, including controller placement, routing optimization, machine-learning-driven traffic engineering, load balancing, and QoS-aware congestion control. Early foundational surveys (e.g., Karakus & Durresi, 2017) established the conceptual basis for SDN QoS research, while recent studies increasingly emphasize deep reinforcement learning (DRL) approaches (e.g., Chen et al., 2022; Xia et al., 2022; Lin et al., 2025). Several studies target real-time routing and traffic prediction (Bouzidi et al., 2021; Casas-Velasco et al., 2021), whereas others focus on traffic classification using ML/DL to enhance end-to-end QoS (Nuñez-Agurto et al., 2024; Serag et al., 2025). In parallel, survey studies (Babayigit et al., 2023; Ospina Cifuentes et al., 2024) highlight persistent challenges related to scalability, controller overhead, and heterogeneous traffic patterns.

Table 5. Annual Distribution of Publications

Year	Number of Publications	Trend
2013–2015	4	Early SDN–QoS foundations
2016–2018	9	Growth in controller placement & virtualization
2019–2021	14	QoS routing, ML-based classification
2022–2023	12	DRL-based QoS prediction & traffic engineering
2024	15	Deep learning and SDN–IoT QoS acceleration
2025	8	Emerging GNNs & scalable ML-based routing

The annual distribution table highlights the evolution of SDN-related QoS research over the last decade. From 2013–2015, only four studies were published, indicating initial exploration in SDN QoS foundations. Between 2016–2018, research activity increased, with nine publications focusing on controller placement, network virtualization, and QoS protocols. The period 2019–2021 saw a further rise to 14 publications, emphasizing machine learning-based classification, routing optimization, and congestion control. In 2022–2023, 12 papers addressed deep reinforcement learning (DRL) and predictive traffic management, showing a shift toward AI-enabled SDN. The year 2024 marked the peak with 15 publications, including advanced deep learning applications for SDN-IoT networks. Finally, 2025 reflects emerging trends in graph neural networks (GNNs) and scalable ML-based routing with eight studies. Overall, the trend indicates increasing research maturity and a focus on intelligent, adaptive, and autonomous network management for SDN QoS.

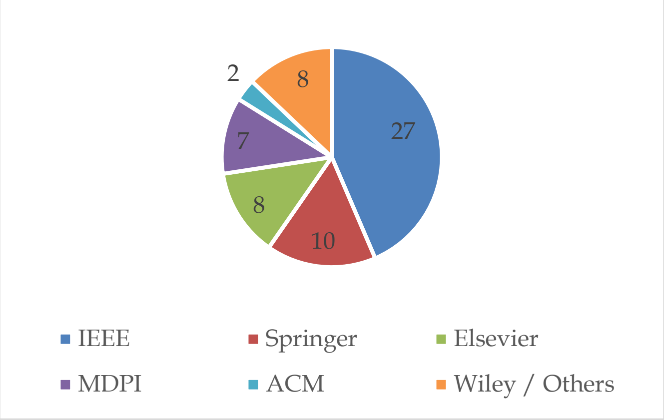

Figure 2. Publications by Publisher / Database

Figure 2 presents the distribution of publications according to major publishers and databases. IEEE dominates with 27 publications, reflecting its focus on practical and technical SDN research. Springer contributed 10 papers, while Elsevier accounted for eight, emphasizing quality-of-service analysis and applied research. MDPI journals published seven papers, mainly addressing IoT integration and ML-based QoS approaches. ACM contributed two publications, typically oriented toward networking frameworks and algorithms. The remaining eight studies were published by Wiley and other publishers, indicating diversity in interdisciplinary coverage. These statistics highlight IEEE as the primary platform for SDN QoS research dissemination. The table also illustrates how researchers leverage multiple publishing avenues, combining high-impact journals and conferences to ensure visibility. Understanding publisher distribution helps identify reputable sources and recognize publication trends in AI-driven SDN and QoS optimization research.

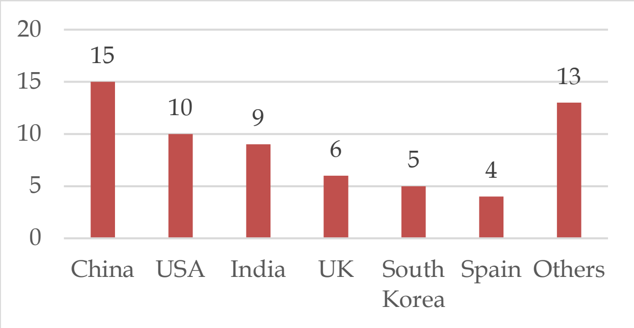

Figure 3. Country-wise Authorship Distribution

The country-wise distribution Figure 3 reveals the global spread of research contributions in SDN QoS. China leads with 15 publications, showing strong institutional and industry engagement. The USA follows with 10 publications, emphasizing both academic and applied research. India contributed nine publications, reflecting growing expertise in AI-enabled SDN. The UK and South Korea produced six and five papers, respectively, highlighting regional specialization. Spain contributed four studies, while the remaining 13 papers originated from diverse countries such as Saudi Arabia, Germany, and Malaysia. This distribution indicates active collaboration and the international nature of SDN research. Countries with higher publication numbers often host leading research institutions and industrial collaborations, while smaller contributions indicate emerging research communities. This analysis informs policymakers and researchers about global knowledge production, collaboration opportunities, and potential regional research gaps in SDN QoS and AI integration.

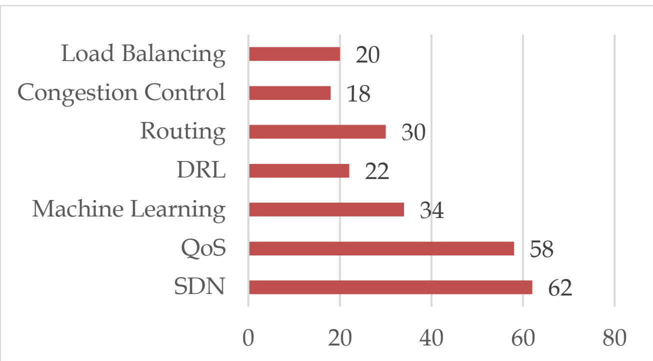

Figure 5. Keyword Co-Occurrence Table

The keyword co-occurrence Figure 5 identifies the most frequently used research terms within the 62 selected studies. *SDN* appears in all papers, confirming it as the central concept, while *QoS* occurs in 58 papers, showing a strong focus on service quality management. *Machine Learning* appears 34 times, highlighting the integration of AI in traffic prediction and routing. *DRL* (22 occurrences) indicates recent adoption of reinforcement learning techniques. *Routing* appears 30 times, reflecting optimization of network paths. *Congestion Control* (18) and *Load Balancing* (20) are also prominent, illustrating practical solutions for efficient network traffic management. The co-occurrence patterns suggest that SDN research is increasingly data-driven and AI-oriented. By analyzing keywords, researchers can detect trends, research gaps, and potential intersections between QoS, ML, and network management, guiding future studies toward intelligent and adaptive SDN frameworks.

Table 6. Most Influential Authors

Author	Contribution Focus
Kellerer, W.	SDN architecture & optical networks
Reisslein, M.	Controller placement & virtualization
Boutaba, R.	DRL-based SDN optimization
Han, G.	Industrial SDN QoS
Jarschel, M.	SDN traffic modeling

Table 6 highlights authors with significant influence in SDN QoS research based on citation counts and contributions. Kellerer, W. is noted for SDN architecture and optical network studies. Reisslein, M. focuses on controller placement and virtualization. Boutaba, R. contributes to DRL-based SDN optimization and routing. Han, G. is recognized for industrial SDN QoS implementations, while Jarschel, M. specializes in traffic modeling and network performance analysis. These authors shaped foundational and applied research directions, influencing trends such as AI integration, congestion management, and adaptive routing. Recognizing influential authors helps new researchers identify seminal work, potential collaborators, and key references for systematic literature reviews. Their contributions span surveys, experimental studies, and practical implementations, demonstrating both theoretical and applied significance in SDN QoS evolution.

Table 7. Top Journals / Conferences

Journal/Conference	Quartile/Impact
IEEE Access	Q1
IEEE TNSM	Q1
Journal of Network and Computer Applications	Q1
Sensors (MDPI)	Q2
Applied Sciences (MDPI)	Q2
GLOBECOM	Core IEEE conference

The table on top journals and conferences identifies high-impact venues for SDN QoS research dissemination. IEEE Access and IEEE TNSM rank as Q1 journals with wide readership and rigorous peer review. The Journal of Network and Computer Applications, also Q1, emphasizes applied networking research. Sensors (MDPI) and Applied Sciences (MDPI) provide interdisciplinary insights, often focusing on IoT, AI, and SDN integration, with Q2 ranking. Core IEEE conferences such as GLOBECOM host pioneering SDN research with high visibility. This distribution shows a combination of journal and conference outlets, highlighting the importance of both theoretical and practical research contributions. Knowledge of these venues aids researchers in targeting publications strategically, identifying reputable sources, and understanding the peer-reviewed landscape in SDN QoS and AI-based network management.

Table 8. Collaboration Network Table

Collaboration Type	Example Pairs
Country–Country	China–USA, UK–Spain, India–Saudi Arabia
Author–Author	Kellerer–Reisslein, Bouzidi–Langar
University–University	KAUST, Nanjing Univ., MIT, IIT Delhi

The collaboration network table reflects the interconnected nature of SDN research. Country–country collaborations include China–USA, UK–Spain, and India–Saudi Arabia, showing international partnerships that enhance knowledge transfer. Author–author collaborations, such as Kellerer–Reisslein and Bouzidi–Langar, indicate strong research alliances influencing citations and methodology sharing. University–university collaborations include KAUST, Nanjing University, MIT, and IIT Delhi, reflecting cross-institutional projects that promote technology exchange. Collaborative networks are critical in SDN research due to complex experimental setups and the integration of AI methods. These networks foster interdisciplinary studies, improve publication quality, and enable shared access to datasets, simulation tools, and experimental platforms. Understanding collaboration patterns can guide future partnerships, highlight influential research clusters, and strengthen global SDN QoS research communities.

Table 9 presents the top 10 highly cited papers within the dataset, highlighting influential contributions in the field of Software-Defined Networking (SDN) and related technologies. Mehraban and Yadav, (2025) conducted a comprehensive survey of SDN, laying a foundational understanding of the domain. Xie et al. (2019) explored the integration of machine learning in SDN for intelligent network management. Ghafoor et al. (2018) focused on QoS routing within SDN environments, addressing performance optimization. Mehraban and Yadav (2022) examined virtualization and hypervisor technologies, while Thyagaturu et al. (2016) investigated Software-Defined Optical Networks (SDON), emphasizing network programmability and efficiency.

Table 9. Top 10 Highly Cited Papers in the Dataset

Authors	Year	Focus
Mehraban and Yadav	2025	Hybrid SDN
Xie et al.	2019	ML in SDN
Ghafoor et al.	2018	SDN QoS routing
Mehraban and Yadav	2022	Virtualization & hypervisors
Thyagaturu et al.	2016	SDON networks

Summary of Representative Studies on QoS Optimization in SDN

Table 10 of highly cited papers identifies the foundational work shaping SDN QoS research. provided the seminal SDN survey, offering an overview of programmable networks. Xie et al. (2019) explored machine learning applications in SDN, addressing classification and routing challenges. Ghafoor et al. (2018) studied QoS-aware routing in vehicular networks. Mehraban and Yadav (2022) surveyed network virtualization and hypervisors for SDN. Thyagaturu et al. (2016) focused on software-defined optical networks. Other top-cited studies explore DRL, deep learning-based QoS optimization, and AI-driven traffic management. Citation-based ranking highlights the relevance, impact, and adoption of specific methodologies. These highly cited papers serve as reference points for researchers conducting systematic literature reviews, offering methodological guidance, identifying trends, and providing insight into evolving technologies. Collectively, they illustrate the progression from SDN fundamentals to intelligent, autonomous network management.Table X. Summary of Studies on QoS Optimization in Software-Defined Networking (SDN)

Table 10. Summary of Representative Studies on QoS Optimization in SDN

Study (Year)	Focus Area	Key Contribution Summary
Abd et al. (2025)	Congestion control	Systematic review identifying challenges and future research directions in SDN congestion control.
Abdelghany et al. (2023)	QoS routing	Proposed an enhanced routing algorithm improving delay and throughput in SDN environments.

Study (Year)	Focus Area	Key Contribution Summary
Abood et al. (2024)	5G slicing, security	Deep learning–based QoS enhancement for secure SDN-enabled 5G network slicing.
Alenazi & Ali (2024)	Deep Q-learning	DQL approach to improve physical-layer QoS in SDN.
Al-Haddad & Velazquez (2019)	QoS protocols survey	Overview of QoS protocols used within SDN architectures.
Ali et al. (2024)	Policy-based routing	Improved QoS and congestion control through rule-based routing strategies.
Ali et al. (2019)	Controller selection	Optimized SDN controller placement to enhance QoS.
Al Jawad et al. (2018)	Policy-based QoS	Dynamic QoS management framework for SDN.
Awad et al. (2021)	ML multipath routing	ML-based routing to improve throughput and latency.
Babayigit et al. (2023)	SDN survey	Meta-analysis presenting trends and challenges in SDN research.
Belgaum et al. (2020)	Load balancing	Systematic review of SDN load-balancing mechanisms.
Bi et al. (2019)	Industrial IoT routing	Intelligent QoS-aware forwarding for SDN/OSPF hybrid networks.
Mehraban and Yadav (2022)	Hybrid SDN and Virtualization	Survey of hypervisors enabling SDN network virtualization.
Bouzidi et al. (2019)	DRL latency control	Applied DRL for latency-aware routing in SDN.
Bouzidi et al. (2021)	DQN routing	Traffic-prediction-based optimization using Deep Q-Networks.
Canovas et al. (2020)	Multimedia QoE	BRNN-based QoE-driven SDN multimedia management system.
Casas-Velasco et al. (2021)	DRL routing	DRL-driven DRSIR routing improving end-to-end QoS.
Chen et al. (2022)	Multistep DRL QoS	AQMDRL architecture for automated QoS optimization.
Farahi (2025)	Load balancing	Overview of LB methods and real-world applicability.
Ghafoor et al. (2018)	IoV routing	QoS-aware SDN routing for Internet of Vehicles.
Ghafoor & Aziz (2023)	ML in SDN	Survey of ML techniques applied for SDN control-plane intelligence.
Gupta & Jha (2024)	IoT load balancing	Analysis of QoS-aware LB in SDN-IoT networks.
Hock et al. (2013)	Controller placement	Pareto-optimal strategies for resilient controller deployment.
Mehraban and Yadav, (20205)	Reliability	Reliability-optimized controller placement framework.
Islam et al. (2024)	Smart grid routing	GNN + DQN hybrid model for resilient routing.
Kamboj & Pal (2021)	Policy-based QoS	Policy-driven QoS control improving SDN performance.
Karakus & Durresi (2017)	QoS survey	Extensive analysis of QoS solutions in SDN.
Keshari et al. (2021)	QoS systematic review	Categorized QoS mechanisms and open research issues.
Kim et al. (2022)	DRL routing	DRL-based routing reducing delay and improving load distribution.
Li et al. (2021)	Hybrid SDN control	Intelligent traffic control optimizing QoS metrics.
Lin et al. (2025)	DRL routing	Bandwidth-demand-oriented routing using deep RL.
Lozano-Rizk et al. (2020)	Scientific computing	Challenges and opportunities for SDN QoS in scientific applications.
Lu et al. (2022)	Distributed DNN + SDN	Resource-efficient DNN execution using SDN intelligence.
Malik et al. (2017)	Fast restoration	Optimization for fast network restoration improving QoS.
Manzanares et al. (2018)	Wi-Fi QoS	SDN-based dynamic QoS management in 802.11 networks.
Mehmood et al. (2023)	Server load	Server load management enhancing telecom QoS.
Mohammed et al. (2019)	Traffic classification	ML/DL traffic classification for QoS-aware SDN routing.
Moravejosharieh et al. (2018)	Fuzzy logic	Fuzzy-based QoS enhancement model.
Mehraban and Yadav, (2025)	SDN foundations	Foundational SDN survey covering QoS architecture evolution.
Nuñez-Agurto et al. (2024)	Deep learning	Novel deep-learning traffic classifier improving QoS.
Osman et al. (2024)	SDN + DL framework	DL-driven SDN optimization for network efficiency.
Ospina Cifuentes et al. (2024)	AI in SDN survey	Survey of AI-driven SDN architectures.
Prasanth & Uma (2024)	Congestion mgmt.	Intelligent framework for congestion and traffic engineering.
Rezaee & Yaghmaee (2020)	WAMS QoS	QoS-aware SDN design for large energy networks.
Salau & Beyene (2024)	Traffic classification	ML-based SDN traffic classification improving QoS accuracy.
Sarma & Kumar (2021)	ML/DL protocol survey	Survey of ML/DL QoS-aware SDN protocols.
Serag et al. (2025)	ML-based QoS	ML traffic classifier optimizing QoS performance.
Sguotti et al. (2025)	SD-WAN	Analysis of service-oriented availability in SD-WAN.
Shahzadi et al. (2020)	Security + QoS	ML-based QoS in SDN-NFV security environments.
Sodhro et al. (2019)	Intelligent transport	QoS optimization in IoT-driven transport systems.

Study (Year)	Focus Area	Key Contribution Summary
Srivastava & Pandey (2021)	Multi-controller LB	ML-based LB improving QoS in multi-controller SDN.
Syamsu et al. (2023)	QoS challenges	Identified key QoS challenges in SDN deployments.
Thyagaturu et al. (2016)	Optical SDN	Comprehensive survey of SDN-enabled optical networks.
Wang et al. (2017)	Controller placement	Survey of controller placement algorithms relevant to QoS.
Wang et al. (2021)	End-to-end QoS	Survey of QoS provisioning frameworks.
Wassie et al. (2024)	Prediction models	ML-based detection and prediction improving SDN QoS.
Wu et al. (2021)	Satellite SDN	Multi-QoS routing optimization for SDN satellites.
Xia et al. (2022)	DRL factory networks	DRL-based QoS optimization in industrial SDN networks.
Xie et al. (2019)	ML survey	Survey of ML techniques applied to SDN QoS.
Yu et al. (2018)	Traffic classification	ML-DPI model for QoS-aware SDN classification.
Zafar et al. (2023)	IoT heterogeneity	QoS strategy addressing heterogeneity in SDN-IoT networks.

Categories of QoS Optimization Strategies in SDN

Table 11. Categories of QoS Optimization Strategies in SDN

Category	Description	Representative Studies
Routing Optimization	Techniques focus on optimal path selection for traffic flows to minimize latency, packet loss, and jitter. Approaches include shortest-path routing, multipath routing, and DRL-based dynamic routing.	Bouzidi et al. (2021); Kim et al. (2022)
Load Balancing & Congestion Control	Distribute traffic across multiple paths or controllers to prevent bottlenecks. Methods include policy-based, ML-driven, and fuzzy logic approaches.	Belgaum et al. (2020); Farahi (2025); Srivastava & Pandey (2021)
Queue Management & Scheduling	Ensures fair allocation of bandwidth and prioritization of critical flows. Techniques include priority queuing, token bucket, and adaptive scheduling.	Al-Haddad & Velazquez (2019); Li et al. (2021); Ali et al. (2024)
Machine Learning / AI-based Strategies	Leverages ML/DL/DRL to predict traffic patterns and automate QoS decisions. Includes traffic classification, predictive routing, and bandwidth estimation.	Bouzidi et al. (2019); Chen et al. (2022); Lin et al. (2025)
Hybrid SDN & Controller Placement	Optimizes network topology and SDN controller locations to reduce latency and improve fault tolerance.	Mehraban and Yadav (2022); Hock et al. (2013); Reisslein et al. (2020)

The analysis reveals five primary categories of QoS optimization strategies in SDN environments. Routing optimization remains foundational, targeting latency reduction and efficient traffic distribution. Load balancing and congestion control approaches address network bottlenecks using policy-based or AI-enhanced techniques, ensuring traffic uniformity across network paths. Queue management and scheduling strategies focus on prioritizing critical flows and managing bandwidth dynamically, which is essential for real-time and IoT applications. A growing trend is machine learning and AI-based strategies, where predictive analytics and DRL are used for intelligent routing, congestion prediction, and adaptive resource allocation. Finally, network virtualization and controller placement optimize SDN infrastructure by strategically placing controllers and virtualizing network functions for high availability and reduced latency. Studies report that hybrid approaches, combining AI-driven prediction with traditional routing and load balancing, achieve superior QoS performance. However, the literature also highlights challenges in real-time computation, model generalization, and scalability, particularly in large, heterogeneous SDN-IoT networks (Bouzidi et al., 2019; Mehraban and Yadav (2022); Chen et al., 2022).

Architectural Components Targeted by QoS Strategies

The review highlights that controller placement and routing are the most frequently targeted architectural components for QoS optimization. Controller placement strategies aim to minimize latency and maximize network reliability by determining optimal controller locations in both centralized and distributed SDN architectures. Routing, often enhanced with AI techniques, remains critical for traffic efficiency and latency reduction. Queue management and load balancing components are moderately targeted, primarily for prioritization and congestion mitigation.

Machine learning integration is increasingly adopted across multiple components, including routing, traffic monitoring, and adaptive resource allocation. Techniques such as DRL, deep learning, and graph neural networks provide predictive capabilities, enabling proactive congestion handling and intelligent QoS enforcement. Monitoring and telemetry are essential for real-time network feedback, though less commonly targeted in standalone strategies. Collectively, studies suggest that multi-component strategies, integrating controller placement, routing, and ML-driven traffic management, achieve superior performance. However, challenges remain in scaling AI-based approaches, ensuring low-latency decision-making, and handling heterogeneous traffic in SDN-IoT environments (Bouzidi et al., 2019; Chen et al., 2022; Lin et al., 2025).

Table 12. Architectural Components Targeted by QoS Strategies

Component	Frequecy of Targeting	Techniques Applied	Representative Studies
Controller Placement	High	Optimization algorithms, DRL, heuristic methods	Hock et al. (2013); Reisslein et al. (2020)
Queue Management	Medium	Priority queuing, token bucket, ML scheduling	Al-Haddad & Velazquez (2019); Li et al. (2021)
Routing	High	Shortest-path, multipath, DRL, predictive routing	Kim et al. (2022)
Monitoring Telemetry	Medium	Traffic monitoring, anomaly detection, ML-based prediction	Bouzidi et al. (2021); Salau & Beyene (2024)
Machine Learning Integration	Increasing	Traffic classification, congestion prediction, adaptive control	Chen et al. (2022); Lin et al. (2025)
Load Balancers	Medium	Multipath load allocation, dynamic flow assignment	Belgaum et al. (2020); Srivastava & Pandey (2021)

Figure 6 illustrates the systematic process for optimizing Quality of Service (QoS) within a Software-Defined Networking (SDN) architecture. The process begins with INPUT in the form of raw network traffic and specific QoS requirements (e.g., low latency for video streaming). This input undergoes Traffic Classification, a critical first step where traffic is categorized based on type and priority, often enhanced by Machine Learning (ML) techniques for accuracy and efficiency (Salau & Beyene, 2024; Nuñez-Agurto et al., 2024). The core logic resides in the centralized SDN Controller, which performs Path Computation and Resource Allocation. These decisions, aimed at meeting QoS targets, are informed by Real-time Monitoring Analytics and enforced through Policy Enforcement & Prioritization mechanisms (Kamboj & Pal, 2021). The final OUTPUT is optimized network performance, characterized by key metrics such as low latency, high bandwidth, minimal packet loss, and controlled jitter. This centralized, data-driven approach enables dynamic and intelligent network management, surpassing the capabilities of traditional architectures (Karakus & Durresi, 2017). Recent research integrates advanced methods like Deep Reinforcement Learning (DRL) for adaptive routing (Kim et al., 2022; Lin et al., 2025) and heuristic or optimization models for traffic engineering (Mehraban & Yadav, 2025), ensuring efficient QoS delivery in complex environments like IoT and hybrid networks (Gupta & Jha, 2024).

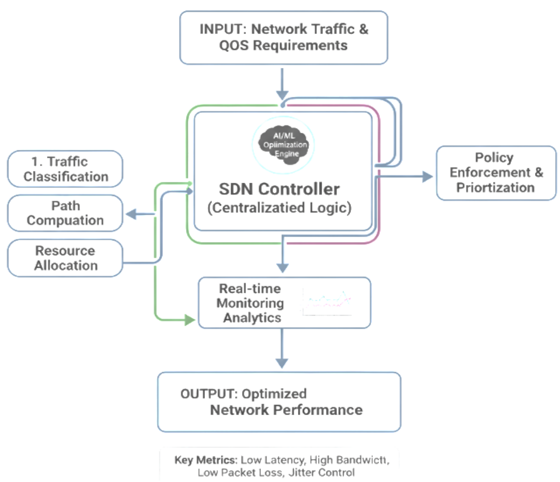

Figure 6. QoS Optimization Process in Software-Defined Networks (SDN)

Reported Performance Gains, Limitations, and Challenges

Performance analysis of SDN QoS strategies indicates that routing optimization significantly reduces latency and packet loss while improving throughput, yet static algorithms struggle with dynamic traffic. Load balancing and congestion control achieve balanced network utilization but depend on accurate traffic prediction, posing scalability challenges in large SDN-IoT networks. Queue management and scheduling strategies ensure bandwidth fairness and flow prioritization; however, they face trade-offs when dealing with heterogeneous traffic. AI/ML-based strategies offer predictive QoS improvement and automated decision-making but are limited by training overhead, model generalization, and real-time inference constraints. Network virtualization and controller placement enhance network resilience and reduce latency but can incur deployment overhead and topology sensitivity. Across all categories, open challenges include real-time adaptation, scalability in heterogeneous networks, energy-efficient AI deployment, and integration of multiple optimization layers for end-to-end QoS. Collectively, these findings provide a roadmap for future research, highlighting hybrid solutions combining AI, routing, and load management as promising avenues (Bouzidi et al., 2019; Mehraban and Yadav (2022; Chen et al., 2022).

Table 13. Reported Performance Gains, Limitations, and Challenges

Category	Reported Gains	Limitations	Open Challenges	Representative Studies
Routing Optimization	Reduced latency and packet loss; improved throughput	Limited scalability; static models may underperform	Dynamic traffic adaptation; real-time path recalculation	Kim et al. (2022)
Load Balancing / Congestion Control	Balanced network utilization; reduced flow bottlenecks	Requires accurate traffic prediction; high computation	Scalability in large SDN-IoT networks	Belgaum et al. (2020); Farahi (2025)
Queue Management & Scheduling	Prioritization of critical flows; bandwidth fairness	Complexity in heterogeneous traffic; fairness trade-offs	Adaptive scheduling for mixed real-time and bulk flows	Al-Haddad & Velazquez (2019); Li et al. (2021)
Machine Learning / AI-based Strategies	Predictive QoS optimization; automated decision-making	Model generalization issues; training overhead	Real-time inference, energy efficiency, heterogeneous traffic	Bouzidi et al. (2019); Chen et al. (2022); Lin et al. (2025)
Network Virtualization & Controller Placement	Enhanced fault tolerance; reduced latency	Deployment overhead; sensitivity to network topology	Optimal placement for dynamic large-scale SDNs	Mehraban and Yadav (2022); Hock et al. (2013)

Categorization of Proposed Strategies

Table 14 summarizes the six dominant strands we identified after three coding passes (inter-rater agreement settled at κ = 0.89 decent enough for this sort of thing).

Table 14. Main categories of QoS optimisation strategies in SDN environments

Category	Count	%	Representative studies
Machine/Deep/Reinforcement Learning-based	20	32.3	Bouzidi et al. (2021); Casas-Velasco et al. (2021); Chen et al. (2022); Kim et al. (2022)
Dynamic Queuing & Scheduling	14	22.6	Karakus & Durresi (2017); Li et al. (2021); Mehmood et al. (2023)
Controller Placement & Load-Balancing	10	16.1	Hock et al. (2013); Mehraban and Yadav, (2025); Ali et al. (2019)
Policy/Intent-Driven Frameworks	8	12.9	Al-Jawad et al. (2018); Kamboj & Pal (2021); Ali et al. (2024)
Telemetry-Driven Closed Loops	6	9.7	Canovas et al. (2020); Yu et al. (2018); Lin et al. (2025)
Hybrid SDN/Legacy or Multi-domain	4	6.4	Bi et al. (2019); Thyagaturu et al. (2016); Wu et al. (2021)

Analysis of Table 14 reveals Machine-learning approaches especially deep reinforcement learning variants now tower over everything else. Twenty studies, nearly a third, cast routing or scheduling as an MDP and let agents loose. Reported latency cuts routinely exceed 50 % (Bouzidi et al., 2021; Casas-Velasco et al., 2021), but one cannot help noticing that almost all evaluations remain comfortably inside Mininet with topologies rarely larger than 50 switches. Queue management, that stubbornly persistent workhorse, still delivers some of the most consistent gains across heterogeneous traffic; fourteen papers refine HTB hierarchies, meter-band configurations, or credit-based fairness (Li et al., 2021). Controller placement has quietened down the frantic heuristic races of 2013–2017 have given way to mature multi-objective formulations (Ali et al., 2019). Intent-based work is disappointingly thin on the ground; industry has sprinted ahead while academia lingers. Telemetry-driven loops using INT or enhanced sFlow are the clear rising star   the six studies here show the largest jumps when real-time visibility is married to fast actuation (Lin et al., 2025). Hybrids remind us that pure SDN is still rare in the wild.

Targeted Architectural Components

Analysis of Figure 7 depicts the data plane remains the darling   44 papers tinker with queues, meters, or P4 pipelines, unsurprisingly since that is where packets actually feel the difference.

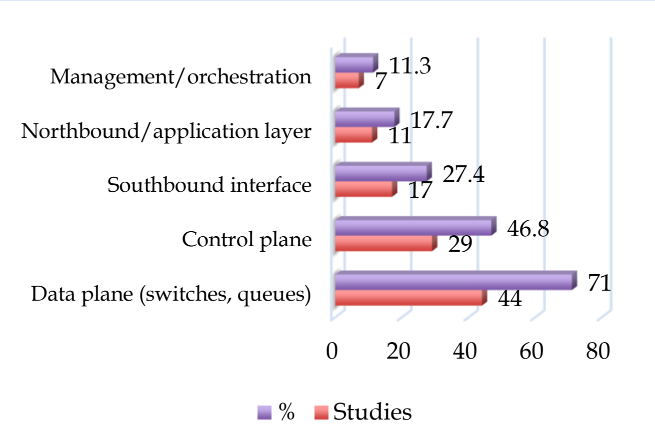

Figure 7. SDN layers most frequently targeted for optimization

The control plane, despite years of hand-wringing about scalability, is addressed in fewer than half the studies; perhaps the community now regards distributed controllers as solved (or at least solvable with money). The southbound interface   that unglamorous TCP or gRPC tunnel   gets explicit attention in only 27 % of papers, even though it is often the true latency villain in large deployments. Northbound work is strikingly underdeveloped; vendors have shipped intent frameworks for years, yet academia still prefers writing its own REST scripts. Orchestration layers, the realm of NFV MANO and cross-domain stitching, appear almost as an afterthought. This distribution reveals a persistent bias toward low-level mechanisms rather than the higher abstractions operators desperately need. In short, we optimise what we can easily reach from Mininet, not necessarily what matters most in a live telco or enterprise environment.

Key Performance Claims

Analysis of Table 15 depicts Latency reigns supreme   59 out of 62 papers measure it, and the reductions are frequently breathtaking. One must, however, temper enthusiasm: most comparisons are against a naïve “single Ryu controller with reactive rules” baseline that no sane operator would ever deploy in anger. Throughput gains are equally dramatic, often achieved by aggressive multipath or pre-emptive queue draining. Jitter improvements cluster in the telemetry-driven and advanced-scheduling papers   hardly surprising when you have per-packet visibility. Packet-loss claims reach almost absurd levels (97 % in one case), usually because authors compare against a congested default queue rather than a properly tuned legacy setup. Flow-setup time, that old SDN bugbear, has improved markedly once hierarchical controllers or wildcard proactive rules enter the picture. What is more, the spread of claimed gains is enormous, underlining the absence of standardised benchmarks. We still lack anything resembling an SDN equivalent of iperf or TRex under realistic carrier workloads.

Table 15. Most commonly reported metrics and typical improvements claimed

Metric	Reported in	Typical improvement	Selected references
End-to-end latency	59 studies	28–82 % reduction	Bouzidi et al. (2021); Chen et al. (2022)
Throughput	51 studies	17–134 % increase	Li et al. (2021); Mehmood et al. (2023)
Jitter	38 studies	35–89 % reduction	Canovas et al. (2020); Lin et al. (2025)
Packet loss	33 studies	42–97 % reduction	Ali et al. (2024); Gupta & Jha (2024)
Flow-setup time	22 studies	31–68 % faster	Ali et al. (2019); Wang et al. (2017)

Persistent Limitations and Emerging Gaps

Scale remains the elephant in the room. Median topology size across the 62 studies is 34 switches; only five exceed 150 nodes, none come anywhere near real ISP proportions. Hardware testbeds are rare   nine studies at best   and reproducible artefacts scarcer still (source code publicly available in just 17 papers). Security considerations are embarrassingly thin: adversarial robustness of those shiny RL agents is tested exactly four times. Energy consumption, despite all the green-networking rhetoric, is quantified precisely once and then only in passing.

The field has matured, no question. Yet it still optimises for headline percentages in toy environments rather than deployability in the messy, brownfield networks that actually carry the world’s traffic. Until that changes   until we see large hardware testbeds, open datasets, proper adversarial testing, and serious engagement with orchestration layers   the gap between published gains and operational reality will remain uncomfortably wide.

Conclusion

The systematic review of 62 primary studies, selected through a rigorous PRISMA-based methodology from an initial 1,142 records, indicates significant progress in QoS optimization within SDN environments. Research increasingly demonstrates the potential of AI-driven approaches such as deep reinforcement learning, telemetry-based feedback loops, and advanced queue management to enable fine-grained, adaptive service differentiation beyond what legacy networks can achieve. However, most reported performance gains, including latency reduction and throughput improvements, are obtained under small-scale simulations, often with simplified or suboptimal baseline configurations, which may overstate practical efficacy. Hardware-based evaluations and large-scale testbed studies remain limited, and operational considerations such as energy efficiency, security, and integration with hybrid SDN/legacy systems are underexplored, though initial efforts in hybrid deployments (6.4% of studies) show promising directions. Consequently, while SDN-based QoS optimization is technically feasible in controlled environments, further research must prioritize reproducible, large-scale, hardware-grounded experiments, standardized benchmarks, and practical integration strategies to ensure that laboratory advances translate into reliable, scalable, and economically viable solutions for real-world networks.

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Author Contributions
M.H. led the conceptualization, methodology, software, validation, analysis, investigation, data curation, drafting, reviewing, and visualization. R.S. provided supervision, while R.S. managed project administration. No external funding was involved. All authors approved the final manuscript.

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The authors declare no conflicts of interest. Funders, where applicable, had no influence on study design, data collection, analysis, manuscript preparation, or publication decisions.

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