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Systematic Review of Software-Defined Networking Congestion Control: Challenges and Future Directions

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Abstract:

The surge in 5G, IoT, and cloud computing has made network congestion management a major challenge. Traditional networking architecture struggles with dynamic traffic, but Software-Defined Networking (SDN) is a novel networking technology by centralized control that offers a solution. This is the first systematic review that categorizes SDN congestion control into ML-driven, heuristic, and rule-based methods, assessed using Mininet, Ryu, and key metrics like throughput and latency. Despite progress, scalability, real-time adaptability, and energy efficiency remain challenges. The study highlights AI integration, solution development, and field testing as future directions, paving the way for path optimization and congestion control in SDN.

Keywords: Software-Defined Networking (SDN), Congestion Control, Machine Learning (ML), Network Optimization, Artificial Intelligence (AI)

الملخص:

أدى النمو المفاجئ لشبكات الجيل الخامس (G5)، وإنترنت الأشياء (IoT)، والحوسبة السحابية إلى زيادة هائلة في حركة مرور البيانات على الشبكة، مما زاد من صعوبة التعامل مع الازدحام. وتعجز الشبكات التقليدية عن تلبية هذه المتطلبات المتغيرة. وتُعد الشبكات المُعرّفة بالبرمجيات (SDN) حلاً مثاليًا، إذ تفصل طبقات البيانات عن طبقات التحكم، مما يُتيح إدارة مركزية ومرنة لحركة البيانات. لذا، يستعرض هذا الاستطلاع 82 ورقة بحثية صدرت بين عامي 2014 و2024، ويُصنّف أساليب التحكم في الازدحام القائمة على الشبكات المُعرّفة بالبرمجيات (SDN) إلى نماذج قائمة على التعلم الآلي (ML)، ونماذج استدلالية (قائمة على التحسين)، ونماذج قائمة على القواعد. وتهدف هذه الدراسة إلى تحديد أكثر الخوارزميات وأدوات المحاكاة شيوعًا التي يستخدمها الباحثون العاملون في هذا المجال. كما تناقش الدراسة الاتجاهات الناشئة، وتحدد اتجاهات البحث المستقبلية للتحكم في ازدحام الشبكات المُعرّفة بالبرمجيات (SDN). ومن الأدوات الشائعة المستخدمة في هذه الدراسات: Mininet (محاكي الشبكة) وRyu (وحدة تحكم الشبكات المُعرّفة بالبرمجيات). لقد أكدنا أن الأساليب القائمة على التعلم الآلي مرنة للغاية ومناسبة للبيئات سريعة التغير مثل الجيل الخامس وإنترنت الأشياء. تستهدف الأساليب الاستكشافية تحسين الأداء من خلال التحسين، بينما تُعد الأساليب القائمة على القواعد أكثر ملاءمة لظروف الشبكة الثابتة. ومع ذلك، لا تزال هناك حاجة إلى معالجة مشكلات مثل قابلية التوسع، واستهلاك الطاقة، والمعالجة في الوقت الفعلي. بشكل عام، تُظهر الشبكات المعرفة بالبرمجيات (SDN) إمكانات واعدة لتحسين التحكم في الازدحام في الشبكات الحديثة. لذلك، تقدم هذه الدراسة نظرة عامة شاملة على التحكم في ازدحام الشبكات المعرفة بالبرمجيات (SDN)، وتقدم توصيات للباحثين والممارسين الذين يسعون إلى تحسين شبكات الجيل التالي.

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الكلمات المفتاحية: **الكلمات المفتاحية:** الشبكات المعرفة بالبرمجيات (SDN)، التحكم في الازدحام، التعلم الآلي (ML)، تحسين الشبكات، الذكاء الاصطناعي (AI).

پوختە

گەشەسەندنی لەناکاوی تۆڕەکانی G5 و IoT و کۆمپیوتەری هەوری هاتوچۆی تۆڕەکانی زۆر زیاد کردووە، ئەمەش وایکردووە مامەڵەکردن لەگەڵ قەرەباڵغیدا زیاتر چالاک بێت. تۆڕە نەریتییەکان شکست دەهێنن لە جێبەجێکردنی ئەو جۆرە داواکارییە گۆڕاوانە. SDN چارەسەرێکی گونجاوە بە جیاکردنەوەی چینەکانی داتا و کۆنترۆڵ بەجۆرێک کە بەڕێوەبردنی هاتوچۆی ناوەندی و هەروەها لاستیکیی دەبێتە شتێکی مومکین. بەم شێوەیە، ئەم ڕاپرسییە پێداچوونەوە بە 82 توێژینەوە دەکات کە لە نێوان ساڵانی 2014-2024 دەرچوون و شێوازەکانی کۆنترۆڵکردنی قەرەباڵغی لەسەر بنەمای SDN وەک مۆدێلی بنەمادار بە فێربوونی ئامێر (ML)، هێوریستی (بە پشتبەستن بە باشکردن) و بنەمای یاسا پۆلێن دەکات. ئامانجی ئەم توێژینەوەیە دەستنیشانکردنی باوترین ئەلگۆریتم و ئامرازەکانی هاوشێوەکردنە کە لەلایەن توێژەرانی کار لەم بوارەدا بەکارهێنراون. سەرەڕای ئەوە، توێژینەوەکە باس لە ڕەوتە سەرهەڵداوەکان دەکات و ئاراستەکانی توێژینەوەی داهاتوو بۆ کۆنترۆڵکردنی قەرەباڵغی SDN دیاری دەکات. هەندێک لەو ئامرازە باوانەی کە لەم جۆرە لێکۆڵینەوەدا بەکاردەهێنرێن بریتین لە Mininet (network simulator) و Ryu (SDN controller). ئێمە پشتڕاستمان کردۆتەوە کە شێوازەکانی بنەمای ML زۆر نەرم و نیان و گونجاون بۆ ژینگە خێرا گۆڕاوەکانی وەک G5 و IoT. شێوازە هێوریستییەکان باشترکردنی کارایی دەکەنە ئامانج بە باشکردن، لە کاتێکدا شێوازە بنەمادارەکانی یاسا زیاتر گونجاون بۆ بارودۆخی تۆڕی ئیستاتیک. سەرەڕای ئەوەش، کێشەکانی وەکو قەبارەدانان، بەکارهێنانی کارەبا و پرۆسێسینگ لە کاتی ڕاستەقینەدا هێشتا پێویستن چارەسەر بکرێن. بەگشتی SDN بەڵێنێکی گەورە نیشان دەدات بۆ باشترکردنی کۆنترۆڵکردنی قەرەباڵغی لە تۆڕە مۆدێرنەکاندا. بۆیە، ئەم توێژینەوەیە تێڕوانینێکی گشتی گشتگیر لە کۆنترۆڵکردنی قەرەباڵغی SDN دەدات، پێشنیارەکان بۆ توێژەران و پزیشکان دەخاتە ڕوو بە ئامانجی باشترکردنی تۆڕەکانی نەوەی داهاتوو.

کلیلە وشە: تۆڕی پێناسەکراوی نەرمەکاڵا (SDN)، کۆنترۆڵکردنی قەرەباڵغی، فێربوونی ئامێر (ML)، باشکردنی تۆڕ، زیرەکی دەستکرد (AI).

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Introduction

For modern communication systems, network congestion has become one of the most limiting factors as data requirements continue to grow. Traditional traffic shaping methods, load balancing, and Quality of Service (QoS) are used to manage flow and prioritize applications in conventional network systems [1]. Software-defined networking (SDN) takes this further by amalgamating the control and data planes and implementing a centralized and programmable traffic system [2]. Moreover, SDN, which separates the control plane from the data plane, simplifies control, enhances flexibility in network management, and presents an excellent opportunity for machine learning [3]. Additionally, open APIs like OpenFlow allow for rapid adaptation to network conditions, particularly in Next-Generation Wireless Networks (NGWNs).

Continuously, the SDN controller gathers information about network states and topologies and makes real-time decisions to optimize performance. As the user bases of video streaming, real-time applications, and cloud-based services expand, congestion control remains a significant issue [4] [5]. Consequently, load balancing (LB) serves as the next step in optimizing traffic distribution across various pathways, which reduces overall throughput. However, existing mechanisms are not stringent enough to adapt to real-time network conditions [6].

Studies have described the use of ML-based methods that predict network congestion and suggest optimized resource allocation by employing heuristic techniques that enable efficient rule-based optimizations [7] [8]. This review, therefore, focuses on SDN congestion control by examining ML-enabled, heuristic, and rule-based approaches, identifying their strengths, highlighting shortcomings (e.g., scalability, response time), and recommending areas for further research. By synthesizing evidence from 82 studies spanning 2014 to 2024, this paper provides a comprehensive overview of SDN congestion control, offering insights for researchers and practitioners aiming to optimize next-generation networks. The paper proceeds with Related Works (Section 2), Methods (Section 3), Results (Section 4), Discussion (Section 5), Conclusion (Section 6), and References.

Related Works

This section organizes SDN congestion control research into three distinct categories.

Machine Learning-Based Techniques

ML and AI improve SDN by predicting traffic patterns and optimizing routing. Akhtar et al. demonstrated ML's success in short-term traffic forecasting, though deep learning models require large datasets and significant computational resources. Nandhini et al. applied ML to scheduling in distributed systems, enhancing fault tolerance but noting scalability constraints [9]. These studies underscore ML's potential and limitations in dynamic network management.

2.2 Heuristic and Optimization-Based Techniques

Heuristic methods leverage mathematical models to enhance SDN performance. Hafeez et al. addressed TCP incast congestion in data centers, showcasing SDN's traffic engineering potential while highlighting scalability limitations [10]. Hodaei et al. discussed heuristic-based congestion

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control, acknowledging its computational overhead in real-time applications [11]. These approaches balance efficiency and practicality but face deployment challenges.

2.3 Rule-Based Approaches

Traditional rule-based methods, such as shortest-path routing and round-robin load balancing, offer simplicity but lack adaptability. Mousa et al. surveyed SDN load balancing, emphasizing metrics like throughput, delay, and response time [12]. This technique provides foundational solutions yet struggles with complex, dynamic traffic. Table 1 shows the summary of related works. Table 1: Summary of Related Works

Table 1: Summary of Related Works

Reference	Advantages	Limitations
[12]	AI-based congestion prediction	Needs quality data; limited scalability
[10]	ML-based scheduling and load balancing	Oversimplifies systems; lacks hybrid focus
[11]	Tackled TCP congestion with SDN	Limited to TCP and data centers
[13]	Surveyed SDN traffic management with ML	Simulation-reliant; lacks real-world testing
[9]	Categorized SDN techniques and metrics	No practical implementation
Proposed approach	Analyzed SDN congestion control and tools	Broad research gaps; technical complexity

Methodology

This review assesses SDN congestion control strategies by analyzing algorithm performance and metrics. A search (2014–2024) spanned IEEE Xplore, Springer, and ACM, applying inclusion/exclusion criteria for relevance and quality.

Research Questions and Motivations

The study addresses the following questions (Table 2):

Table 2: Research Questions and Motivations

Research Question	Motivation
What are the primary challenges in SDN congestion control?	Improve SDN efficiency and scalability
How do ML-driven techniques compare to heuristic and rule-based methods?	Identify the most effective approach
What limits current SDN algorithms in real-world deployment?	Ensure practical solutions
How can AI/ML enhance SDN congestion control?	Optimize intelligent management
What role do hybrid approaches play?	Enhance robustness and adaptability
What are emerging trends and future directions?	Guide innovation for 5G and IoT

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Data Collection and Selection Criteria

Articles were sourced from major publishers (Table 3).

Table 3: Database sources

Publisher	URL
IEEE Xplore	https://ieeexplore.ieee.org/
Springer	https://link.springer.com/
Science Direct	https://www.sciencedirect.com/
ACM	https://www.acm.org/
Wiley Online Library	https://onlinelibrary.wiley.com/
Arxiv	https://arxiv.org/list/cs.AI/recent
MDPI	https://www.mdpi.com/
Semantic Scholar	https://www.semanticscholar.org/
Research Gate	https://www.researchgate.net/
Taylor & Francis	https://www.tandfonline.com/
Google Scholar	https://scholar.google.com/

Search Strategy

The review targeted SDN congestion control and load balancing papers from 2014–2024, using keywords like "SDN congestion control" and "machine learning" (Table 4).

Table 4: List of Strings and Keywords

String	Batch1	Batch2	Batch3
String 1	Software-Defined Networking	Congestion Control	Network Congestion
String 2	Software Defined Networking	Artificial Intelligence	Congestion Control
String 3	SDN	Machine Learning	Congestion Control
String 4	SDN	Optimization	Congestion Control

Quality Assessment

The research papers were evaluated for their quality based on the prescribed criteria for their inclusion and exclusion. A preliminary examination of the executive summaries of the papers was conducted and based on our guiding research questions the paper was included or excluded. As shown in table 5

Table 5: Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Research focuses on SDN congestion control and critical decisions	Research unrelated to SDN congestion control
Articles in English	Articles in other languages
Published between January 2014 and December 2024	Review/survey papers and duplicates excluded

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Articles Selection Process

The article selection process began with research question formulation and search string development. Only English-language papers (2014–2024) relevant to SDN congestion control were included. An initial 445 articles were filtered through four stages, reducing to 82 final papers based on duplicates, relevance, and full-text analysis. Figure 1 demonstrates the scanning process.

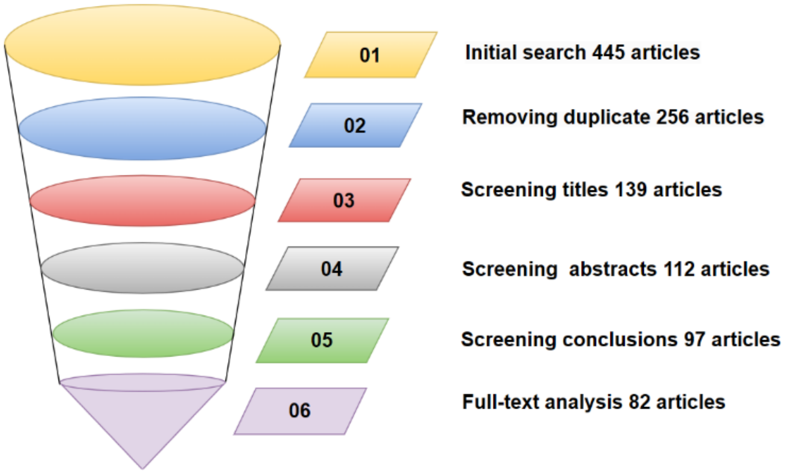

Fig 1: Scanning Process

Figure 1 represents the **Scanning Process** used to filter and select relevant articles for the study. Here's a breakdown of each step and its effectiveness:

1. **Initial Article Collection (445 Articles)**
   - **Effectiveness**: Provides a **broad dataset**, ensuring a **comprehensive** literature review.
2. **Stage 1: Duplicate Removal**
   - **Effectiveness**: Eliminates redundant studies, reducing unnecessary effort in later stages.
3. **Stage 2: Title & Abstract Screening**
   - **Effectiveness**: Quickly filters out **irrelevant** papers, saving time before a deeper review.
4. **Stage 3: Full-Text Analysis**
   - **Effectiveness**: Ensures selected papers contain **valuable insights** and align with the research scope.
5. **Final Selection (82 Papers)**
   - **Effectiveness**: Results in a **high-quality, refined dataset**, ensuring that only the most **relevant, recent, and reliable** studies are included.

Each step refines the dataset, making the literature review **efficient, relevant, and focused** on SDN congestion control.

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Results

Classification of Approaches

SDN congestion control is categorized into three approaches (Figure 2).

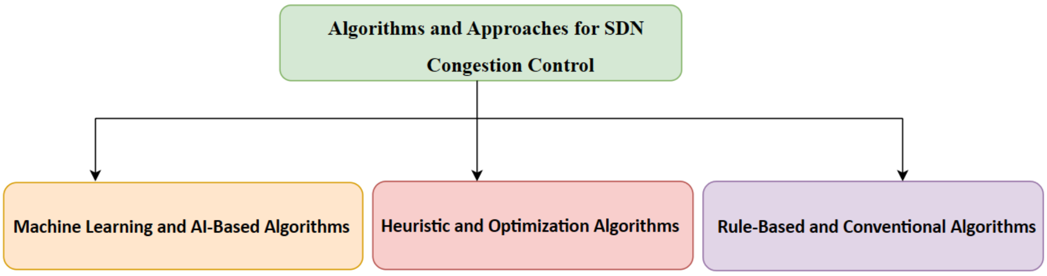

Fig 2: Algorithms and Approaches Classification

Machine Learning and AI-Based Algorithms

They use deep learning, reinforcement learning, and hybrid models to optimize resources through prediction and adaptation. While powerful, challenges include high computational costs and scalability issues [10] [14].

Table 6: ML and AI-Based Summary

Ref/Year	Algorithm/Technique	Simulation Tools	Metrics	Problem Addressed	Limitation
[15], 2024	ML: RNNs, LSTM, Gaussian processes	Mininet, Visual C++, MATLAB	Precision, congestion frequency, latency	SDN load imbalance	High computational cost
[16], 2023	Multi-Agent RL (Q-learning)	Not mentioned	Bandwidth, jitter, throughput	SDN congestion	Evaluation of other RL algorithms
[17], 2020	Adaptive RL with Fuzzy NN	Mininet, NetEm, Wireshark	Goodput, packet loss, bandwidth	IoT congestion in MPTCP	Training time and delays
[18],2021	RL (Q-learning, TCP-CA/RL)	Mininet, OpenAI Gym	Data transfer time, throughput	TCP inefficiency in data centers	Binary reward function
[19], 2020	Multi-task DRL	Mininet, Python RLlib	RTT, throughput, fairness	SDN congestion	Model opacity, guidance algorithms
[20],2021	PRSNN, ANN	Python, Mininet	PLR, NEC, throughput	SDN-IoT congestion	Scalability, delays
[21],2022	LSTM, BiLSTM, GRU	Mininet, Ryu	MAE, RMSE, congestion counts	SDN traffic prediction	High computational power

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[22], 2023	Neural networks, PCoDeL	Mininet, Bmv2	Accuracy, throughput, jitter	QoS in SDN	P4 language constraints
[23], 2019	DDPG, CNN, RL	OMNET++	Delay, packet loss	SDN routing inefficiency	Limited topologies
[24],2023	ML: Clustering, regression	Mininet	Throughput, delay, packet loss	Data center congestion	Scalability, adaptability
[25], 2018	LSTM RNNs	TensorFlow/Keras	MSE	Traffic matrix prediction	Relies on historical data
[26], 2023	H2O clustering, Autoencoder, ML models	Mininet, Google Colab	Accuracy, MSE	Elephant flow prediction	Lack of real testbed integration
[27], 2020	Bayesian network, RL	Python 3.6	Delay, load balance, convergence	SDN load balancing	Scalability in large networks
[28], 2024	DNN, CNN, RF	Mininet, Ryu, TensorFlow	Accuracy, throughput	Elephant flow management	Single dataset testing
[29], 2021	Q-learning	Mininet, VMware	Link utilization, bandwidth	SDN congestion	Lack of algorithm comparison
[30], 2021	CNN, LSTM, Conv-LSTM	Deep learning	MSE, training loss	Traffic trend prediction	Dataset generalization
[31], 2024	RF, XGBoost, DQN-CNN	Mininet, Ryu	Throughput, latency, load balance	SDN-DCN load balancing	Limited configurations
[32], 2018	Neural networks, GA, PSO	Spark MLlib	Throughput, latency, resource allocation	SDN/NFV traffic optimization	High computational burden
[33], 2023	Adaptive ML, hybrid load balancing	NS-3.26	Load, packet loss, throughput	SDN load/resource optimization	Communication inefficiencies
[34], 2020	ARIMA, LSTM, MLP	VirtualBox, iPerf3	MAE, MSE	Bandwidth prediction	Traffic variance
[35], 2024	mGRNN, CA-HPO	MATLAB	MAE, RMSE	SDN traffic routing	High computational cost
[36],2022	Naïve Bayes, SVM	Not mentioned	Accuracy, sensitivity	5G/6G congestion	Limited real-world scenarios
[37], 2023	Bayesian Network, DRL	Python, PyTorch	Load ratio, processing delay	SDN load/resource balancing	Large datasets required
[15], 2024	ML: RNNs, LSTM, Gaussian processes	Mininet, Visual C++, MATLAB	Precision, congestion frequency, latency	SDN load imbalance	High computational cost

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[22], 2023	Neural networks, PCoDeL	Mininet, Bmv2	Accuracy, throughput, jitter	QoS in SDN	P4 language constraints
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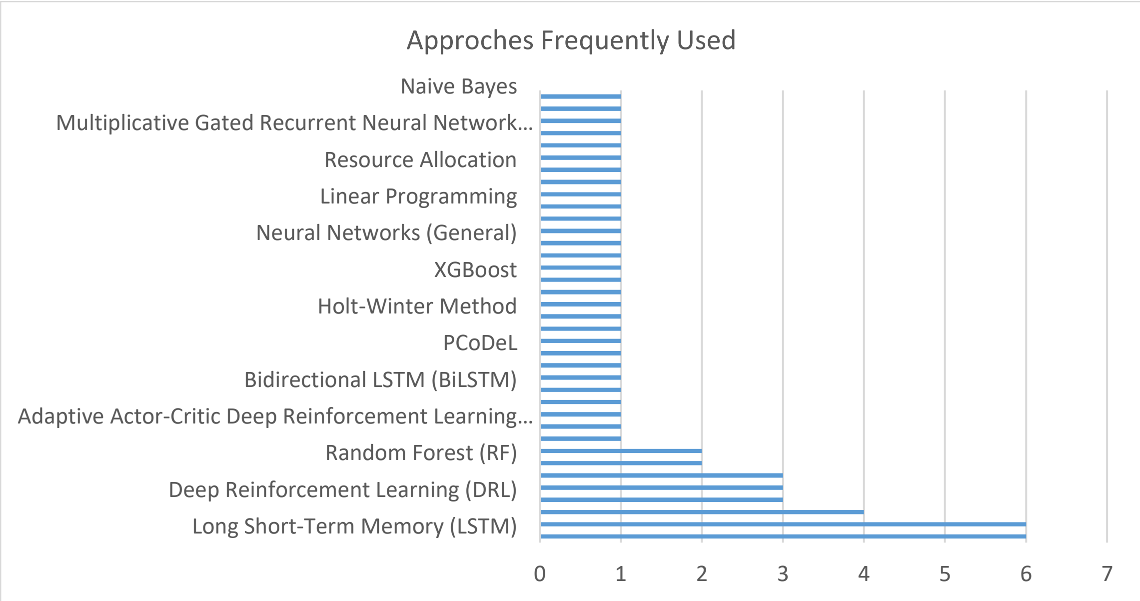

Fig 3: ML and AI Algorithms and Approaches

Fig 3 highlights LSTM and RL as top SDN congestion control methods, with CNN, DRL, and Q-Learning aiding feature extraction and decision-making. RF, Bayesian Networks, and advanced models like BiLSTM and GRU enhance prediction. Optimization techniques like CA-HPO further refine congestion control, showcasing SDN's evolving intelligence.

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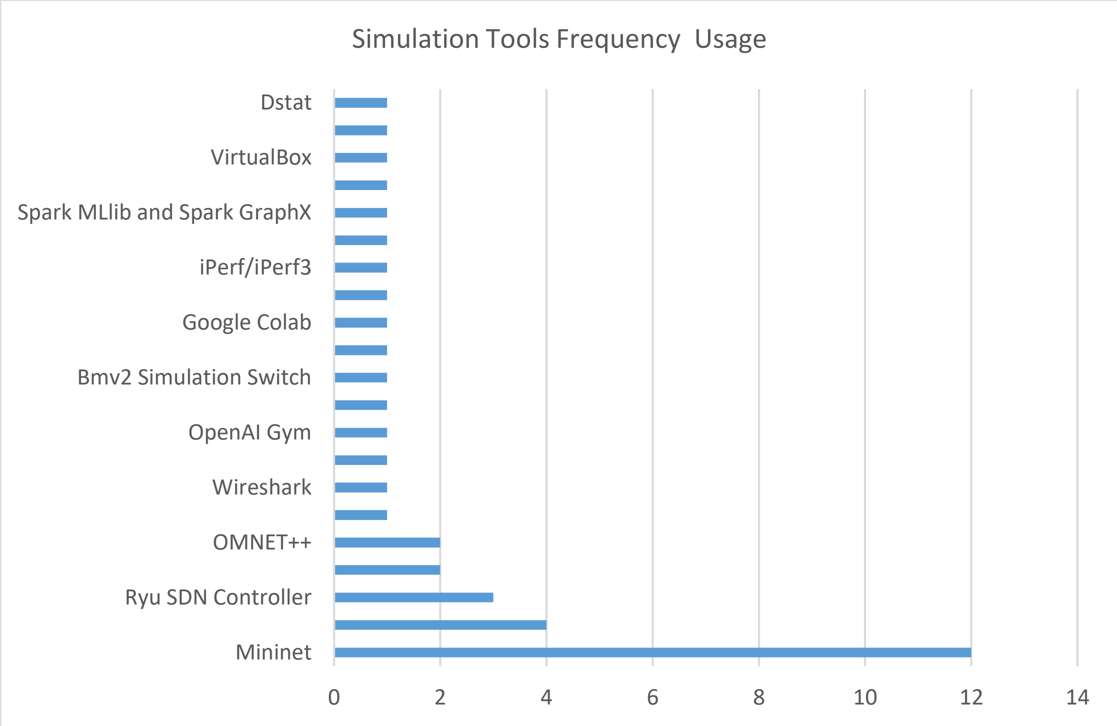

Fig 3: ML and AI Tools

Fig 4 summarizes SDN simulation tools for load balancing and congestion control. Mininet is the most used (12 instances), followed by Python (4) and Ryu (3). MATLAB and OMNET++ (2 each) support modeling. Other tools like Wireshark, TensorFlow, NS-3.26, and cloud-based platforms highlight diverse research approaches. The figure showcases the variety of techniques used in SDN optimization.

Heuristic and Optimization Algorithms

Heuristic methods optimize efficiently but face scalability issues (Table 7).

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Table 7: Heuristic Summary

Ref/Year	Algorithm/Technique	Simulation Tools	Metrics	Problem Addressed	Limitation
[38], 2021	Multipath optimization, active-active links, rerouting.	Ryu, Mininet, Iperf.	Throughput, delay, jitter, packet loss.	Enhance WAN performance and reduce SDWAN costs.	Single-controller topologies.
[39], 2021	Utility-based congestion optimization.	Mininet, OpenvSwitch, Ryu.	Utility, bandwidth, retransmission, RTT.	Congestion control in SDN.	Scalability in large networks.
[40], 2024	Congestion detection, SDN routing, Dijkstra's algorithm.	Mininet, Ryu.	Throughput, utilization, detection time.	MPTCP throughput degradation.	Limited dynamic traffic scenarios.
[41], 2024	Policy-Based Routing, delay optimization.	Mininet, Quagga.	Delay, jitter, throughput, flow time.	QoS and congestion in multimedia networks.	No real-time app communication.
[42], 2021	MRBS, heuristic server/path selection.	Mininet, Python, Floodlight.	Response time, throughput, load deviation.	Load balancing in DCNs.	Traffic spike handling.
[43], 2023	RACC using MHHO, DBSCAN clustering.	MATLAB.	Energy, delay, PDR, mortality rate.	Congestion in WSNs.	No wireless recharging scenarios.
[44], 2017	SP, SWP, MPH for multicast.	Mininet, Ryu, Openvswitch.	Throughput, latency, congestion-resistance.	Multicast inefficiency in SDNs.	Centralized bottlenecks.
[45], 2019	F-DCTCP for fairness and throughput.	OpenFlow SDN.	Throughput, utilization, fairness.	TCP Incast in SDN data centers.	OpenFlow protocol challenges.
[14], 2024	VNR_LBP, profit-based congestion control.	NS2, Floodlight, Mininet.	Throughput, latency, congestion, cost.	SDN congestion.	Scalability in large SDNs.
[46], 2022	Artificial Bee Colony for routing/balancing.	Mininet, SDN Load Balancer.	Routing metrics, path length.	SDN routing inefficiencies.	High computation needs.
[47], 2023	D-PSO with hybrid cost function.	Mininet, POX.	RTT, PLR, throughput.	Congestion and delay in SDNs.	Limited topologies.
[48], 2020	MOABC-GAO for routing optimization.	Mininet, Ryu, OpenFlow.	PLR, RTT, jitter, energy.	SDN load balancing.	Single-controller setups.

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The Scientific Journal of Cihan University – Sulaimaniya PP: 158-184
Volume (9), Issue (1), June 2025
ISSN 2520-7377 (Online), ISSN 2520-5102 (Print)

[49], 2015	Heuristic for timeslot/path allocation.	Packet-level simulations.	Throughput, queue, RTT.	SDN congestion in data centers.	Scaling, overhead issues.
[50], 2022	Multi-objective optimization.	Gurobi, AMPL.	Performance, traffic, queue.	SDN traffic congestion.	No security metrics.

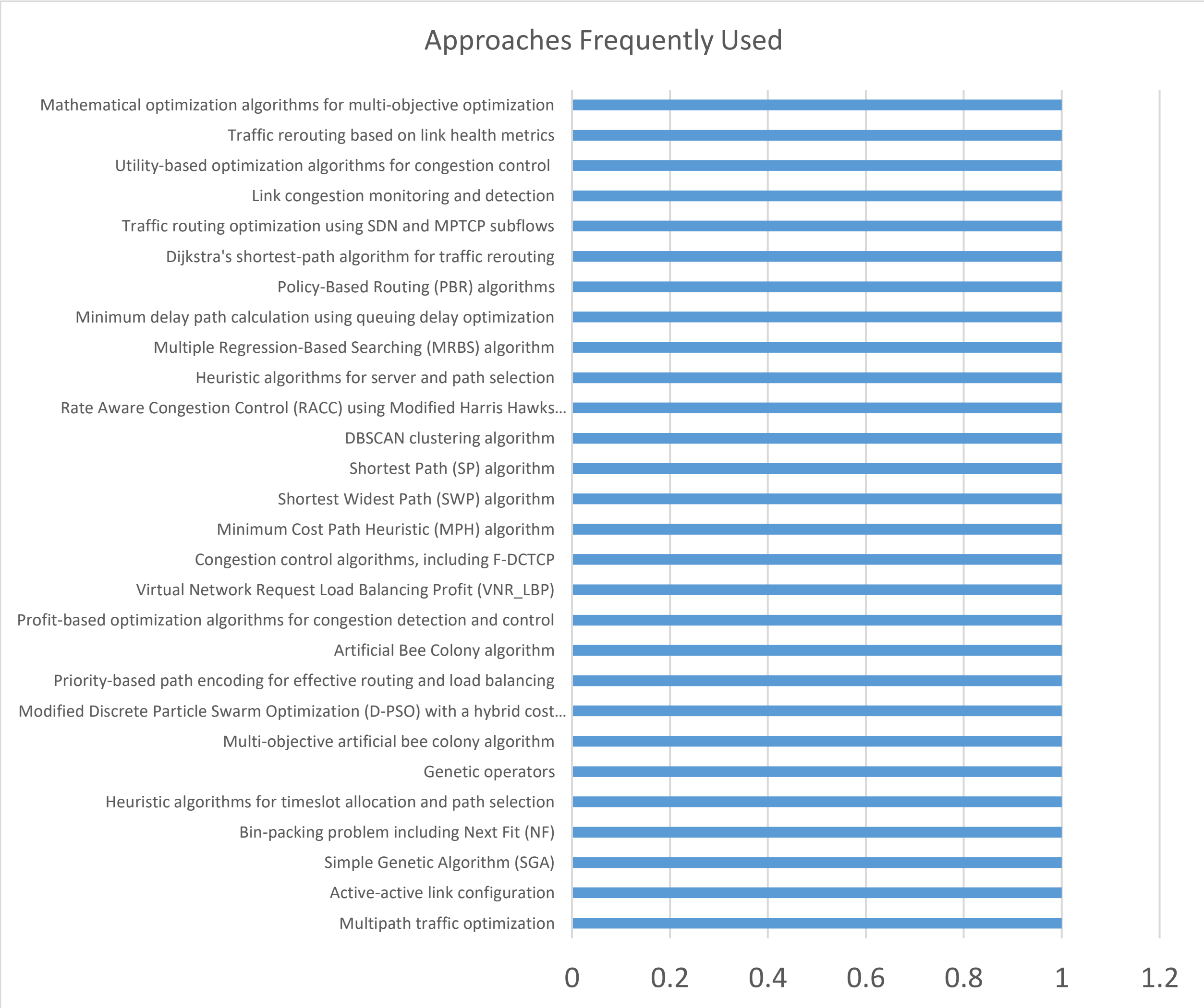

Fig 5: Heuristic Algorithms

Figure 5 provides a broad overview of SDN congestion control algorithms, highlighting diverse approaches without favoring a single method. Heuristic techniques (e.g., genetic operators and ABC) and optimization methods (e.g., D-PSO, mathematical models) are prominent. Specialized algorithms address traffic distribution, queuing delay, and congestion monitoring. The uniform frequency of techniques suggests a need for comparative research to determine optimal solutions for specific network scenarios.

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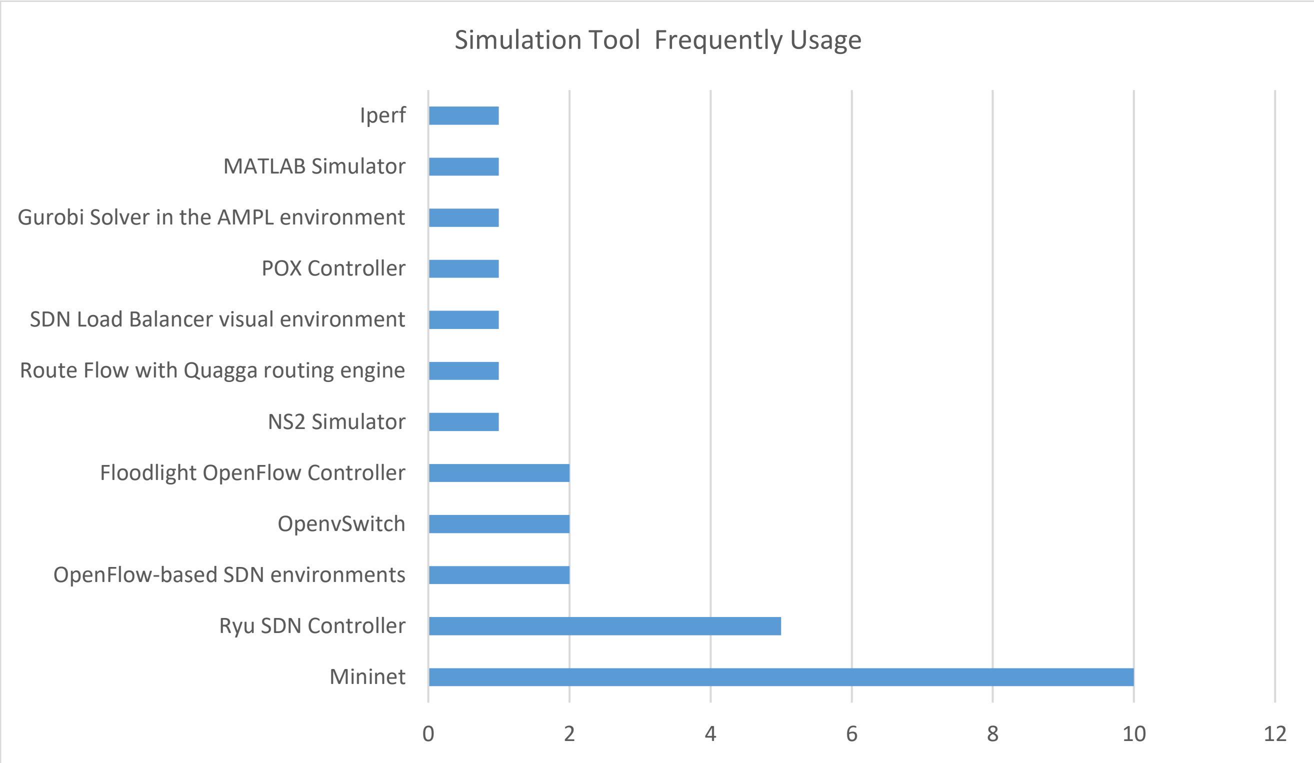

Fig 6: Heuristic Algorithms

Figure **6** ranks SDN simulation tools for load balancing and congestion control by usage frequency. Mininet (10 cases) is the most used due to its SDN simulation capabilities. Ryu (5 cases) is favored for its Python-based flexibility. OpenFlow, OpenvSwitch, and Floodlight (2 cases each) support specific SDN scenarios. Less common tools like NS2, POX, Route Flow, and MATLAB (1 case each) serve specialized functions. The distribution underscores the variety of tools available, with selection depending on research needs.

Rule-Based and Conventional Approaches

Shortest path, round-robin, and static load balancing are simple, cost-effective solutions but lack adaptability in dynamic, heterogeneous networks [10] [14].

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Table 8: Rule-Based Summary

Ref/Year	Algorithm/Technique	Simulation Tool	Metrics	Problem Addressed	Limitation
[51], 2020	Optimal routing, congestion control	Mininet, Ryu, Iperf	Transmission time, throughput, RTT	TCP Incast, congestion in data centers	Simulation limits real-world scenarios
[52], 2020	CAFT, load balancing	ns-3	Flow completion time, throughput	Poor load balancing in asymmetric topologies	Limited diverse workload evaluation
[53], 2018	Bayesian Network, Dijkstra's	Mininet, OpenIris	Packet loss, throughput, delay	Congestion in SDN environments	Controller overhead from traffic monitoring
[54], 2017	Traffic prediction, QoS-aware allocation	MATLAB CVX	Packet loss, link utilization	Resource allocation in dynamic traffic	High complexity for large networks
[55], 2022	Firefly Algorithm	Not mentioned	Delay, delivery ratio, throughput	Congestion in FANETs	Dynamic UAV mobility issues
[56], 2023	LSTM-based link prediction, SARS	Mininet, ONOS	Link utilization, packet loss	Inefficiency in SDN routing	Imbalanced datasets
[57], 2018	Q-learning, Sarsa	Mininet	Congestion control, link utilization	Congestion in SDN data centers	Scalability of Q-matrix
[58], 2022	Decision trees, dynamic load balancing	ns-3	Delivery ratio, latency	Congestion in SDN networks	Scalability in diverse networks
[59],2021	Markov Chain, traffic prioritization	OMNeT++	Cost, congestion, throughput	Load balancing in IoT networks	Complexity in implementation
[60], 2020	SDN-based load balancing	Mininet, Ryu	Throughput, RTT	Congestion in cloud networks	Traffic estimation challenges
[61], 2021	Ant colony algorithm	Not mentioned	Load efficiency, latency	Load balancing in SDN networks	Lack of large-scale testing
[62], 2022	Yen algorithm, incremental learning	Mininet, Ryu	Throughput, delay	Inefficient flow detection	Handling large-scale data

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The Scientific Journal of Cihan University – Sulaimaniya **PP: 158-184**
Volume (9), Issue (1), June 2025
ISSN 2520-7377 (Online), ISSN 2520-5102 (Print)

[63], 2016	Extended Johnson, Bellman-Ford	OMNeT++	Response time, jitter	Congestion in SDN	Scalability in complex networks
[64], 2021	Power-efficient scheduling	Mininet, Ryu	Energy efficiency, MLU	Power saving in SDN	High power in high loads
[65], 2022	Congestion-aware, DDG algorithm	Mininet	Execution time, monitoring	Transient congestion in SDN	Multi-flow update deadlocks
[66], 2024	Sieve mechanism, rate adjustment	ndnSIM	Throughput, stability	Congestion in NDN	Lack of flow prioritization
[67], 2018	QoS schemes, path computation	ns-3, ONOS	Throughput, delay	Resource management in WSN	Controller failure risk
[68], 2017	LLDP-based congestion control	Mininet, ODL	Packet loss, throughput	Congestion in SDN	Limited topology testing
[69],2024	Work-stealing algorithms	OMNeT++	Congestion rate, server performance	Server congestion in SDN	High task granularity challenges
[70], 2016	Rule insertion patterns	PICA8, Floodlight	Latency, RTT	TCAM insertion latency in SDN	No direct solution
[71], 2020	SDCCP, FCA	Mininet	Utilization, queue length, throughput	Inefficient congestion control in networks	Scalability in large networks
[72], 2023	eSDN, dSDN	NetSim	Throughput, delay, jitter	Dynamic network loads, controller overload	Static controller deployment limits
[73], 2024	BRF congestion control	Mininet, OpenDaylight	Bandwidth, fairness, packet loss	Inefficiencies in 5G networks	Complexity in SDN integration
[74],2017	Rate-based, credit-based control	Mininet, Floodlight	Zero loss, link utilization	Packet loss in SANs	Delay sensitivity in credit schemes
[75], 2018	Dijkstra's algorithm	Mininet, OpenDaylight	Throughput, bandwidth	Congestion in SDNs	REST API latency
[76], 2019	Proactive load balancing	Mininet, Ryu	FCT, traffic balance	Uneven load in data centers	Per-flow overhead degradation

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[77], 2014	MP routing, CC	Mininet, Iperf	Bandwidth, throughput	Inefficient bandwidth in DCNs	Single controller failure risk
[78], 2021	Heavy-hitter detection, ECMP	Mininet, BMv2	FCT, routing rules	ECMP inefficiency in data centers	Hybrid probing overhead
[79], 2017	SDTCP	Mininet, Open vSwitch	Goodput, FCT, queue length	TCP incast in data centers	Centralized controller scalability
[80],2014	Load-sensitive path selection	Power Law topology	Delay, throughput	Congestion in SDN	Overhead from OpenFlow protocol
[81], 2015	SDTCP	Mininet, Floodlight	Goodput, query delay	TCP incast congestion	Limited flow type handling
[82], 2024	DA-DCTCP	Mininet, Ryu	Throughput, FCT, latency	Inefficient congestion control	Queue threshold adjustment
[83], 2018	L2RM	Mininet, Ryu	Link utilization, table overflow	Traffic congestion in SDN	Polling delay to link failures
[84], 2019	Load balancing mechanisms	Mininet, POX	Delay, jitter, packet loss	Inefficient traffic distribution	Scalability challenges
[85], 2018	Dijkstra's algorithm	Mininet, Iperf	Latency, bandwidth	Load balancing in SDN	Path availability dependence
[86], 2020	RPS-LB	Mininet	Queue utilization, response time	Cloud congestion from user demand	Single control plane failure
[87], 2022	CATLB	OMNeT++	FCT, Mice/Elephant flows	Congestion in networks	Adapting to different conditions
[88], 2018	Congestion detection	Mininet, Floodlight	Bandwidth, RTT	SDN congestion control	No overall congestion reduction
[89], 2019	Bitrate adaptation	ONOS, DASH.js	PSNR, playback time	Video congestion in SDN Wi-Fi	Limited traffic fluctuation handling
[90], 2024	Multipath routing	Mininet, Ryu	Delay, jitter, packet loss	Reliability in high-traffic SDN	Scalability, real-world conditions

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[91], 2021	Dynamic load balancing	Mininet, Floodlight	Throughput, response time	Resource utilization in SDN	OpenFlow delay in stats
[92],2016	Rate adaptation, feedback control	NS2	Bandwidth, FCT variance	Bandwidth fairness in SDN	Scalability issues
[93], 2023	WFQ, AIMD	NS2	Queue length, goodput	Congestion in SDN	Scalability challenges
[94], 2017	SICC	NS2	FCT, response time	Incast in data centers	Limited real-world testing
[95], 2020	Store-carry-forward	TheONE	Delivery ratio, latency	Opportunistic network congestion	Optimized replication needs

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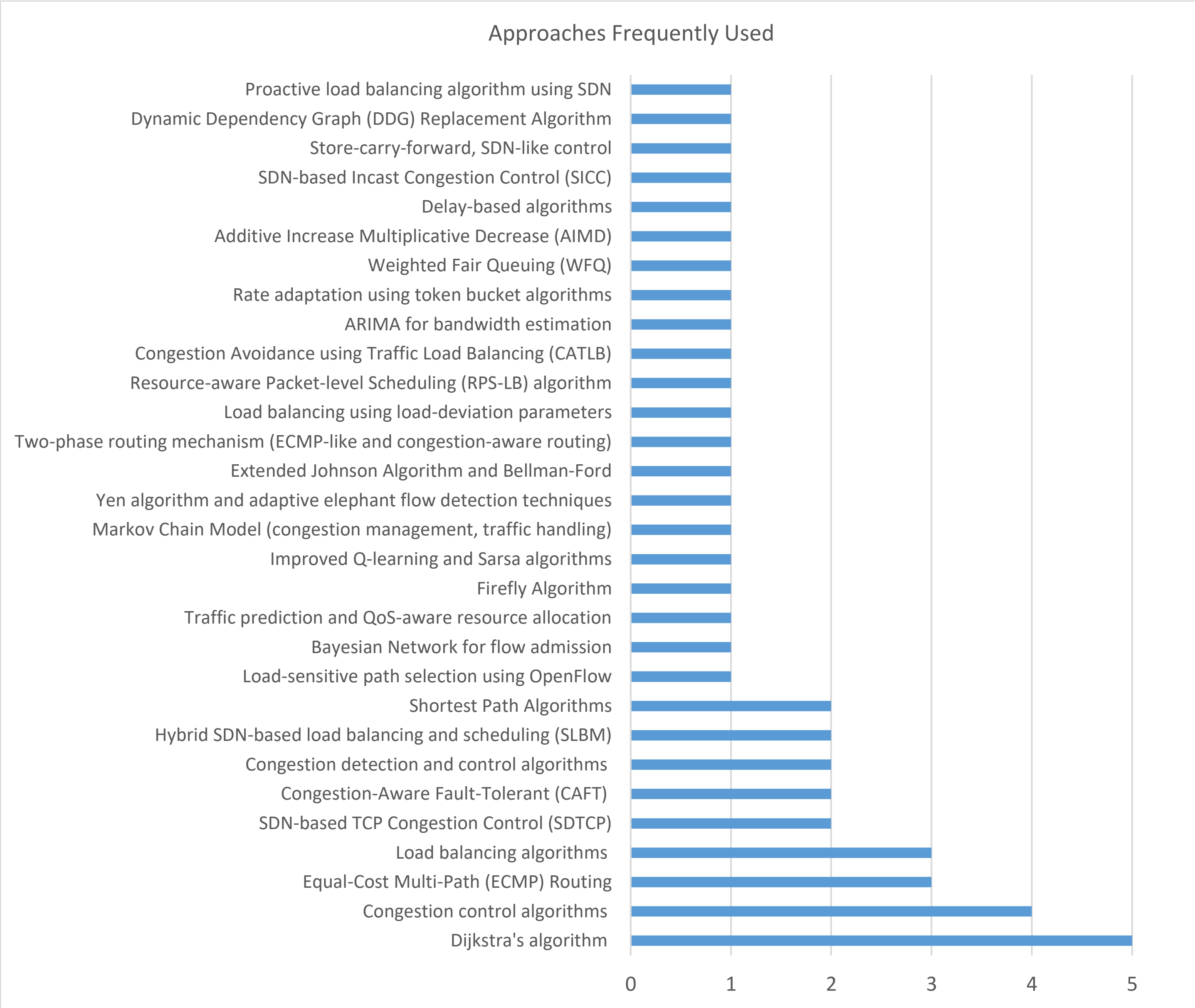

Fig 7: Rule-Based Algorithms

Figure 7 summarizes SDN-based load balancing and congestion control algorithms, with Dijkstra's algorithm (5 uses) as the most popular for shortest path routing. Control algorithms (4 uses) aid adaptive queue management, while ECMP and round-robin (3 uses each) help traffic distribution. SDN-specific techniques like SDTCP, CAFT, and SLBM (2 uses each) enhance network robustness. Emerging methods, including Bayesian networks, Firefly, and ARIMA, highlight the role of predictive modeling and adaptive strategies in SDN congestion management. Combining traditional and SDN-specific techniques is key to handling dynamic network challenges.

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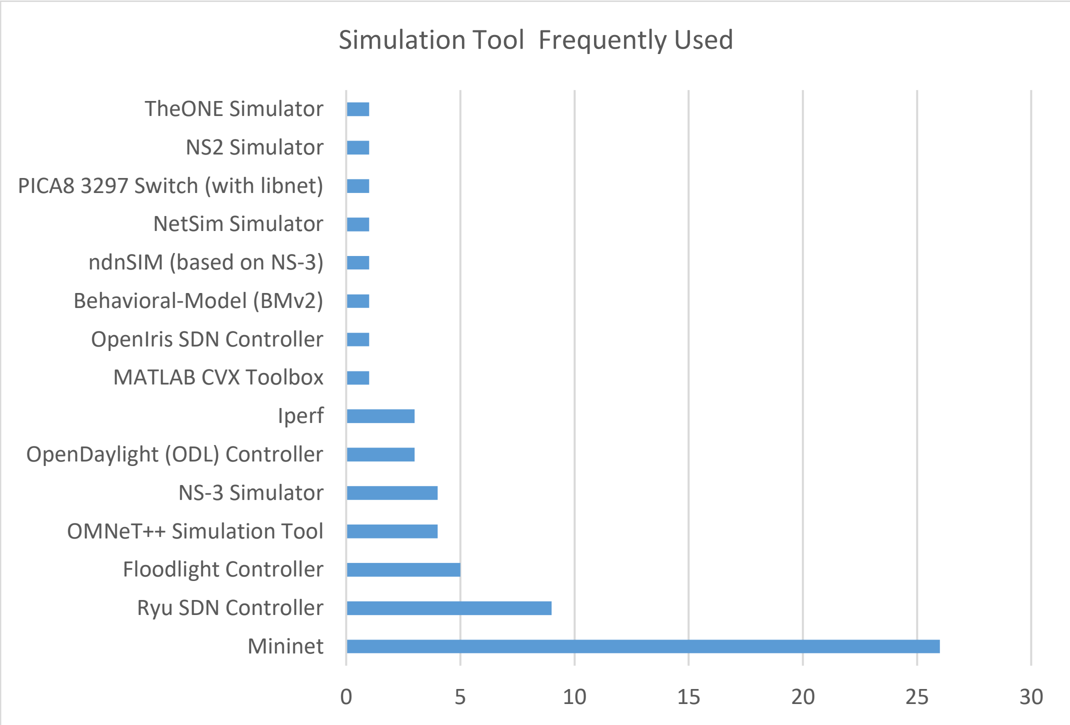

Fig 8: Rule-Based Tools

Figure 8 highlights Mininet (26 mentions) as the top SDN emulator, followed by Ryu (9) for SDN development. Floodlight (5), OMNeT++ (4), and NS-3 (4) serve specific needs, while ODL and Iperf (3 each) aid load balancing. Other tools have niche applications, but Mininet and Ryu dominate SDN research.

Discussion

Performance Comparison and Research Gaps

ML-driven approaches excel in predicting traffic for 5G and IoT but require significant resources, limiting scalability. Heuristics balance efficiency and adaptability, performing well in controlled settings like data centers, yet struggle with real-time shifts due to centralized control. Rule-based methods are simple but inadequate for modern, dynamic traffic. A key gap is the reliance on simulations (e.g., Mininet), which overlooks real-world complexities like hardware failures. Hybrid models combining ML, heuristics, and rules are underexplored, as is energy efficiency—a critical factor for sustainable networks.

Key Insights

Scalability, adaptability, and energy efficiency are persistent challenges. ML offers predictive power, heuristics provide practical optimization, and rule-based methods ensure simplicity, yet each has trade-offs. Hybrid approaches promise robustness by merging strengths, suggesting SDN solutions must align with specific network needs—prediction for dynamic systems, efficiency for constrained ones, or simplicity for static setups.

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Research Gaps and Future Directions

ML-driven approaches excel in predicting traffic for 5G and IoT but Several gaps hinder the evolution of SDN congestion control. The reliance on simulations over real-world deployments limits understanding of how these strategies perform under actual conditions, where factors like equipment variability and unexpected traffic spikes come into play. Hybrid models, despite their promise, are not widely studied, leaving a gap in how best to integrate the strengths of ML, heuristics, and rules to tackle scalability and adaptability together. Energy efficiency, vital for sustainable networking, receives insufficient focus, with few efforts addressing the power demands of modern networks.

Looking ahead, research should shift toward real-world testing to validate findings beyond simulated environments. Developing lighter, less resource-intensive ML models could make predictive techniques more practical, while hybrid frameworks that combine intelligent prediction, efficient optimization, and decentralized control offer a path to balance complexity and performance. Energy-aware solutions, possibly drawing from nature-inspired optimization, should be a priority to support green networking goals. Emerging trends like autonomous control through reinforcement learning distributed controller setups, and technologies such as blockchain for security or edge computing for responsiveness could further enhance SDN's capabilities.

Addressing the Research Questions

This review addresses the core questions driving the study:

What are the primary challenges in SDN congestion control? Scalability, real-time adaptability, and energy efficiency stand out, as they limit performance in large, dynamic networks due to centralized structures and resource demands.

How do ML-driven techniques compare to heuristic and rule-based methods? ML leads in prediction and flexibility, heuristics balance efficiency and practicality, and rule-based methods offer simplicity, with effectiveness varying by network type and conditions.

What limits current SDN algorithms in real-world deployment? Dependence on simulations, scalability issues, and resource-intensive processes prevent practical application and missing real-world complexities.

How can AI/ML enhance SDN congestion control? AI and ML improve traffic forecasting and dynamic management, though their complexity requires simplification for broader use.

What role do hybrid approaches play? Hybrids strengthen responsiveness and versatility by merging strengths but needing further development to scale effectively.

What are emerging trends and future directions? Trends include autonomous learning, distributed control, and sustainable designs, alongside innovations like blockchain and edge computing, guiding SDN's evolution.

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6. Conclusion

This review of 82 studies (2014–2024) highlights Software-Defined Networking's (SDN) potential to transform congestion control through its programmable architecture. ML-driven methods excel in dynamic 5G and IoT settings, heuristics optimize efficiently in specific contexts, and rule-based approaches suit static networks. Yet, simulation reliance, scalability issues, and limited hybrid exploration hinder real-world impact. Future efforts should focus on real-world testbeds, lightweight AI, and hybrid models blending prediction, efficiency, and decentralized control. Innovations like reinforcement learning, multi-controller designs, and energy-efficient solutions are vital for 5G and IoT demands. Robust academia-industry collaboration is key to bridging theory and practice, advancing SDN to reshape network performance.

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