Enhancing Network Congestion Control: A Comparative Study of Traditional and AI-Enhanced Active Queue Management Techniques

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Abstract

The issue of multi-access services based on the rapidly expanding Internet affects communication networks and creates congestion problems in buffers, which require effective control. Buffers have previously been managed using simple algorithms such as Droptail (DT), but this method has proven to have many setbacks, such as large queue delays and frequent occurrences of global synchronizations and shutdowns. To overcome these problems, the Active Queue Management (AQM) technique was introduced, including algorithms like Random Early Detection (RED). AQM techniques predict and discharge packets or label them before the buffer reaches its capacity to prevent congestion. In recent work, these algorithms have been enhanced with deep reinforcement learning to achieve improved network performance. This paper intends to present an evaluation of different studies conducted by researchers on congestion control methods. More importantly, it aims to compare the various findings, highlight the prospects of the different methods amid their weaknesses, and discuss future research opportunities within this critical domain of network management.

Keywords: Random Early Detection; RED; Deep Reinforcement Learning; Machine learning; DRL

1. Introduction

As the size of the network increases, the problem of congestion control becomes a major issue and high priority issue. Thus, with the growth of the Internet and the desire to use the Internet for time-division multiplexed traffic. As for sensitive applications, they require the definition and deployment of novel network architecture to contain better algorithms in congestion control [1]. Traffic buildup is manifested in the network, where several users pray in order to get the access to the common resources, which include bandwidth, buffers and queues. It may lead to a breakdown in network performance, including lengthy end-to-end delays, high packet loss, and the potential for the TCP protocol to collapse as a result of congestion from resending dropped packets [1][2]. Network congestions must be prevented or dealt with as soon as they arise because of the ongoing growth in the pace at which data is transmitted via networks. A queue management system can be used to regulate a channel's queue size [4].

Tail Drop (TD) was one of the first tactics used by TCP networks to address the congestion problem. However, TD has some downsides, including full queue, global synchronization, lock out, and a bias against bursty traffic. To address these issues, a set of approaches known as "Active Queue Management (AQM)" have been developed, primarily to control network congestion early on and ensure a good quality of service for traffic volumes [2]. AQM is an effective policy for controlling buffer bloat and network congestion [3]. In order to do this, a plethora of number of approaches exist, such as Controlled Delay (CoDel) [4], Random Early Detection (RED) [5], and Proportional Integral controller Enhanced (PIE)[6]. AQM algorithms, such as RED, manage packet queues to prevent buffer overflow and mitigate congestion before it becomes severe[7]. The original idea of the RED algorithm is to prevent buffer overflow by early detection in a full queue. For this purpose, RED uses four control parameters, namely, maximum threshold max_{th}, minimum threshold min_{th}, maximum drop probability max_p and weighting of the queue w_q. RED detects the status of emerging congestion by computing the weighted average

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queue length (avg), which is denoted hereinafter as avg, and alerts transmission control protocol (TCP) senders that congestion has occurred by dropping packets deliberately at a certain probability. In the original RED algorithm, the value of minth is 5 and maxth is 15. If avg is lower than minth, then the drop probability of packets will be zero. If avg is higher than maxth, then the drop probability of packets will be one. If avg is higher than minth but still below maxth, then the drop probability of packets will be p(avg)[8]. Primary packet mark probability p(avg) is computed like a linear function for average queue size. The router's buffer has two thresholds (minimum and maximum) that are compared to the computed average to decide when to drop packets. No packet is dropped when the average is less than the minimum threshold, indicating that there is no congestion at the buffer [9]. The dropping probability (Dp) of all incoming packets is computed when the average is between the minimum and maximum thresholds. The packet's estimated Dp alone should be used to determine whether it should be queued or discarded at random [10]. "RED with Reconfigurable Maximum Dropping Probability (RRMDP)," to improve network performance where from the average queue size and queuing latency. The RRMDP algorithm aims to dynamically redefine the maximum dropping probability (maxp) based on the traffic load, enabling better control of the avg and queuing delay without compromising packet dropping rates or link usage [11]. Enhances AQM using neural networks and fractional order techniques. It dynamically adaptation AQM parameters depending on traffic intensity and self-similar factors, average queue length, and packet loss rate are reduced [12]. A Deep Reinforcement Learning AQM (DRL-AQM) that utilizes DRL to understand complex patterns in data flow following training in basic network environments. Where, enhancements to the AQM algorithm can be achieved without the need for parameter adjustments[13].

Recently, DRL can be used to make decisions in the real world, it has become more and more popular. Many researches have applied DRL in networks to address issues including job scheduling, congestion management, and data-driven flow control for wide-area networks. The main goal of this survey is to shed light on how researchers have responded to emerging technological, to organize the research background in a systematic manner based on existing literature, and to identify the key characteristics that define this growing area of research. The main contributions of our work are:

- The implementation of a Deep Reinforcement Learning AQM (DRL-AQM) has shown promise in understanding complex data flow patterns without the requirement for parameter adjustments, ultimately leading to improved performance in network environments.
- Discussing and categorizing the benefits and challenges identified in the literature on RED from 2019 to 2024.
- This review underscores the importance of continued exploration and development in this area to address the growing demands of modern network environments.

This review is divided into five main section. The first section provides an introduction to congestion control and the RED algorithm. The second section outlines the research methodologies, scope, and the process of selecting literature, the process of filtering research articles while cohesively structuring the research background from existing literature. The third section examines the numerical results obtained from the reviewed articles. The fourth section discusses and categorizes the benefits and challenges identified in the literature on RED from 2019 to 2024. The final section concludes the review.

2. Method and Sources information

The research's primary focus is on AQM mechanism specifically employing the RED algorithm, and some of techniques for congestion control, all methods of crowding control and RED were taken into consideration.

Our research relied on the use of three digital databases to collect targeted articles: (1) Google Scholar, which indexes a wide array of research across pure sciences, social sciences, humanities, electronic technologies, and arts; (2) IEEE Explore, an academic database offering a wealth of articles in computer science, electrical engineering, and electronic technologies, (3) Science Direct, which hosts a substantial repository of medical research and scientific methodologies.

These databases collectively offer a comprehensive view of the AQM mechanisms using the RED approach, providing general vision into the available research across a broad spectrum of scientific disciplines.

2.1 Selection of study

The study selection process involved a two-step approach to review the available literature. In the first iteration, irrelevant articles and duplicates were eliminated by reviewing the titles and abstracts. Subsequently, in the second iteration, a more thorough examination of the remaining articles from the first step was conducted to further refine the selection.

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2.2 Searching

The search in "Google Scholar, Science Direct, and IEEE Explore" databases was conducted the start of 2019 by their search boxes. The combination of keywords which contained "Random early detection," "RED," "Deep reinforcement learning," and "DRL" was used in different variations that were combined using "AND" and "OR" operators. Fig. 1 illustrates the exact text of query. In each search engine, the options were utilized for excluding chapters in book and other reports types due to considering conference and journal articles as the two settings that would most likely comprise the latest and applicable scientific articles related to this review.

2.3 Eligibility requirements

Figure 1 presents the articles that were included in the study after meeting the specified selection criteria. The aim was to categorize the research on AQM mechanisms using the RED algorithm for congestion control into four broad groups. These groups were gained from pre-surveying the literature without constraints (the study utilized Google Scholar for obtaining the background and tendencies in literature).

The selection process began with the removal of duplicate articles, followed by the exclusion of articles that did not satisfy the eligibility criteria through skimming and filtering iterations. One of the main reasons for exclusion was articles that were not published in English.

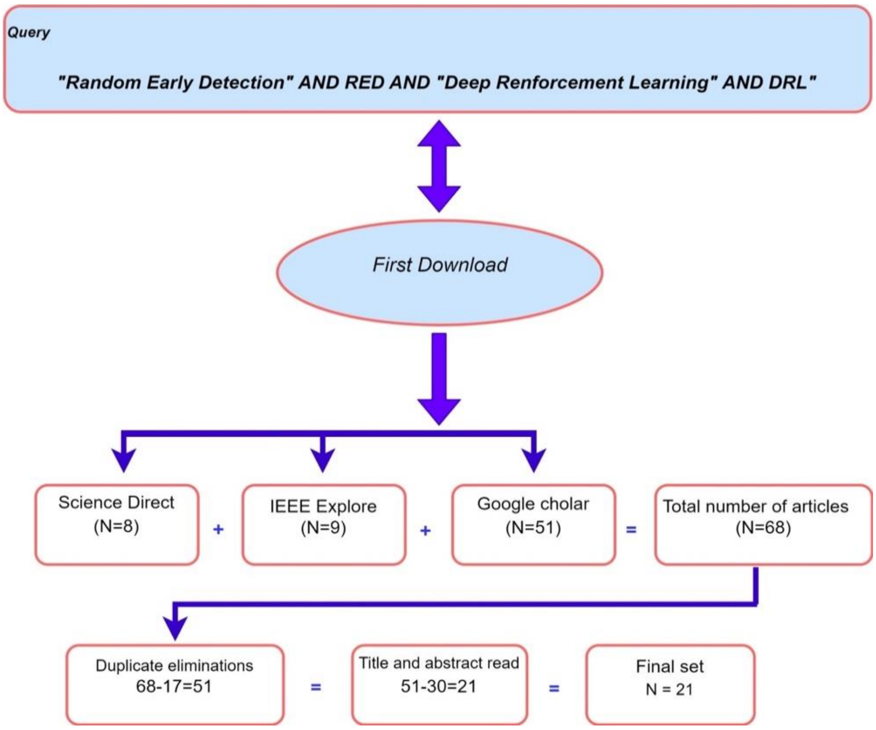

Figure 1. Flow chart of selection of study, including the search query and implication criteria

3. Result

Initial query resulted in 68 papers, namely, from Google Scholar 51, Science Direct 8, and IEEE Explore databases 9. This research adopted refined articles that have been published during the period from 2019 to 2024. Then, they have been organized into (3) categories. In these (3) databases, 17 out of 68 research articles were duplicates. When the research headings and abstracts were scanned, the excluded 30 research articles, and kept a total of 21 articles. Thus, the author kept a total of 21 articles in the last set. All of these articles were associated with different topics on the AQM mechanism to control congestion using the RED mechanism. Figure 2 presents the taxonomy, which was utilized in reviewing the main research streams that focused on the AQM mechanism to control congestion using the RED mechanism.

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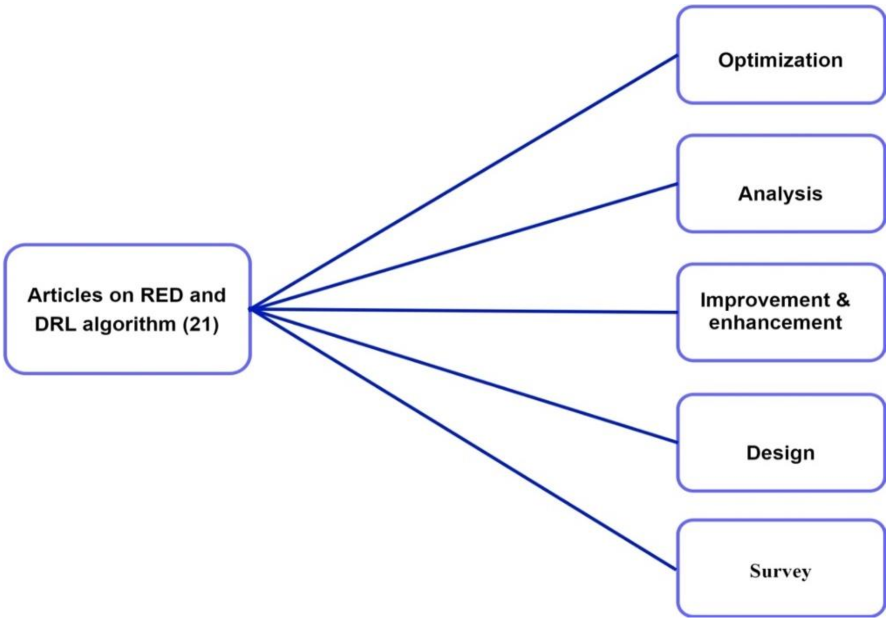

Figure 2. Taxonomy for research literature on random early detection

This classification demonstrates the comprehensive improvement of several applications and studies. It proposes varied classes, evaluation articles related to the AQM mechanism in the control of congestion using the RED mechanism and other. Studies containing actual efforts to improve the AQM mechanism to control congestion using RED. For purpose of statistical analysis, and optimization, the following sections show the observed categories.

3.1 Optimization

Jing and De [15] in 2022 suggests the QP-AQM algorithm, an AQM technique built on the Q-learning traffic predictor. Response times are relatively lag, and congestion levels rise to enhance the ARED and RED algorithms in the highly crowded network. The network traffic is modeled using the Markov decision process, and the traffic is predicted using an enhanced Q-Learning algorithm. The traffic prediction result is then translated into a prediction value for the average queue length, and the prediction result is utilized to adaptively adjust the parameters in the ARED algorithm. This improves the performance of the AQM algorithm, throughput, and latency.so that preserve the excellent performance of the QP-AQM algorithm in networks with high levels of congestion. The limitations lie in the lack of extensive real-world validation, and a thorough comparative analysis with existing AQM algorithms.

Aya and Didem [14] in 2022 proposes Deep Q-Network (DQN) algorithm The algorithm works by balancing two types of utility functions, referred to as rewards:

The delay reward increases with decreased delay time. The enqueue reward increases as the rate of packet drops decreases. The two rewards must be balanced as when most packets are dropped the delay reward will increase whereas if most packets are kept the enqueuer reward will increase but packets may experience very long delays. The balance between the two is controlled using a scale factor parameter δ. It is observed that increasing training data size will increase the performance of the algorithm. The deep reinforcement learning based AQM was found to outperform RED in terms of latency and throughput under many scenarios. The drawback identified in the study is the observed oscillations in round trip time (RTT) the Deep Q-Network (DQN) algorithm. Therefore, the drawback lies in the need to address and mitigate the oscillations in RTT to ensure consistent and stable performance of the DQN algorithm in reducing network delay. This oscillation in RTT is as a challenge and an area for further research to stabilize the performance of the DQN algorithm.

Taewon and Yeunwoong [15] in 2024 propose DeepAAQM, a Using the optimal policy at the front of the queue, a DRL-based algorithm for low-power AQM in IoT WSNs may minimize energy consumption and maintain an AoI value. When formulate a Markov decision process (MDP) model, CH can choose to forward, flush, or leave buffered data from associated cluster member nodes. Then, by applying the DQN method, it can obtain the best policy for DeepAAQM. Where optimizing both AoI and energy consumption enhances the overall performance and efficiency of IoT sensor networks, leading to more reliable data collection and transmission Simulations

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demonstrate that, in contrast to traditional queue management techniques, the DeepAAQM queue management approach may lower CH power consumption while trying not to exceed the AoI value threshold, allowing IoT sensor networks to be stable and ensuring QoS. The DRL model It may suit specific training conditions, which reduces its effectiveness in different world scenarios, Where the model requires substantial data and time to train, this may be an obstacle in scenarios needing quick deployment or with limited data.

Praveen et al [16] in 2023 suggested iCoCoA for CoAP, an intelligent congestion control algorithm that uses a deep reinforcement learning approach to predict and manage congestion in dynamic environments. An application layer protocol used in the Internet of Things, the constrained application protocol (CoAP) reduces the number of retransmissions but does not maximize throughput or adjust to changing conditions. Consequently, a novel algorithm for clever congestion control is put forward. To determine the efficient RTO, iCoCoA takes into account network parameters as the quantity of retransmissions, RTTVAR, Round Trip Time (RTT), and prior Retransmission timeout (RTO). To determine the ideal Retransmission Timeout in order to reduce congestion in dynamic environments. The suggested iCoCoA effectively manages the finite buffer and reduces unnecessary computations the agent must perform throughout the training and operation phases. Additionally, it optimizes energy consumption, throughput, and unnecessary frequent retransmissions. In both continuous and burst traffic scenarios, having been created and tested on the Cooja simulator, iCoCoA outperformed standard protocols like CoAP, CoCoA, and CoCoA+.

Prohim et al [17] in 2022 proposed a multi-agent method to satisfy the relevance of URLLC for mission-critical IoT model services, including PARAA for virtual resource allocation optimization and PICOA for eFL aggregation server offloading recommendations. By using the q-value function, deep neural network (DNN) approximator, and epsilon greedy algorithm balancing exploration and exploitation., MADQNs are able to acquire the highest future long-term reward expectation of joint state spaces. Tensor Flow, Keras, the Bellman equation, and the OpenAI Gym library were used in the development of the custom environment and DQN agent. The goals of multi-agent deep Q-networks (MADQNs) are to support computation offloading choices, optimize resource allocation rules, and impose a self-learning softwarization. For long-term sufficiency, the suggested controller modifies the forwarding rule in a reactive manner. In order to optimize long-term policy, the scheme principally takes into account the criticalities of FL model services and congestion conditions. Based on Quality of Service (QoS) performance parameters such as packet drop ratio, packet drop counts, and packet delivery ratio, latency, and throughput, simulation results showed that the scheme outperformed reference systems. A discrete-event network simulator called ns-3 is used to simulate 5G new radio (NR) networks and provide an end-to-end (E2E) view.

Shahzad et al [18] in 2023 proposed RLECN is a learning-based ECN method that modifies the ECN threshold dynamically in adjust to shifting network circumstances. To address the issue of not determining the optimal value E-CN threshold, where the precise value is selected using testing or estimation. RLECN uses software-defined networking (SDN) to minimizing the TCP acknowledgment response time, therefore enhancing ECN performance. It mainly focuses on three performance metrics: queue occupancy, power function of the connection, and normalized flow completion time (FCT). RLECN is a lightweight solution that doesn't require significant system modifications to be implemented. use SDN to collect network statistics and does not require any offline training. The system is a strong fit for contemporary, dynamic network environments because it uses reinforcement learning (RL) to learn and optimize from real-time input. In comparison to FQ-CoDel and Intelligent AQM, the RLECN operates extremely well through simulation and produces a steady and good bottleneck utilization. It computes the queue usage, channel power function, and FCT and discovered that RLECN outperforms the most advanced SQ-ECN systems in terms of performance.

3.2 Analysis

Ayman et al [2] in 2022 suggested algorithm deep Q-networks (DQN) to solve problem of congestion issues and sent packet drop in the nodes, that happen from increased the traffic used in the networks. Work of four components: drop rate, average queue length, enqueue rate, and dequeue rate. State st is defined at each time step t as st (dequeue rate, enqueue rate, drop rate, and avrg_queue_len), which is the contribution of the multi-facet perceptron (MLP), which is made up of three secret layers, each with 16–32–16 neurons. Drop probability and non-drop are the two probabilities that are returned by the main Q network that is used. In order to achieve efficient network management, the recommended algorithm for deep Q-networks (DQN) relies on reinforcement learning (RL) to minimize drop and delay. So, the results of DQN better than of RED algorithm. This work is primarily focuses on the comparison between the DQN algorithm and the RED algorithm about network efficiency from where managing congestion and packet drops. Where, the study lacks an analysis of the potential challenges associated with the implementation of the DQN algorithm in adaptive queue management systems.

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3.3 Improvement and Enhancement

Majid and Serkan [21] in 2023 introduced a weighted ensemble DRL model for congestion control in Transmission Control Protocol/Internet Protocol (TCP/IP) networks that combines four DRL models: Deep Q-Learning (DQN), Proximal Policy Optimization (PPO), Deep Deterministic Policy Gradient (DDPG), and Twin Delay DDPG (rlTD3). Different action areas are incorporated into models to effectively manage congestion in AQM systems. In both normal and stress testing, the suggested model performed better than single DRL models and well-known congestion control algorithms like RED. To improve the stability and performance of AQM congestion management, the trained DRLs DQN (discrete), DDPG (continuous), rlTD3 (continuous), and PPO (discrete)) are integrated using a weighted average of probability. The study includes drawbacks the complexity and computational resources required for implementing the weighted ensemble approach, this complexity led to increased computational overhead and resource requirements, potentially limiting the practicality of deploying the model in real-world network environments.

Ayman et al [3] in 2022 suggests an AQM RED implemented deep reinforcement learning framework, for effective network control and research the trade-off between queuing latency and throughput. Choose Deep Q-Network (DQN) as the scheme's base. It chooses a packet drop or non-drop operation at the packet departure point depending on the current state, which consists of dequeue_rate, enqueue_rate, drop rate, and average queue length. This technique uses the highest likelihood parameter for the packet reduction using the Q learning algorithm. The learning structure determines the best Network Quality Management System. By doing this, the algorithm will be able to customize the highest likelihood of packet drop, improving network efficiency and avoiding congestion. The DQN algorithm been testing and is applicable in a network to maintain reliability, reduce latency, and increase throughput. Where obtained good and superior outcomes on RED.

Xiaosong et al [19] in 2024 a new algorithm called queue change trend based adaptive RED (QCT-ARED) is proposed. This model can dynamically change the queue weight values based on the consumption rate of every queue adaptively. Tends to use trend analysis to solve the problem of congestion in the network more effectively. Instead of being observant of the fluctuations, the strategy involves the alteration of the network parameters based on the changes in the averages of the queue length hence coming up with a proactive approach towards congestion. The latter is also the ability to differentiate between transient and persistent congestion and thus provides better stability of a network resulting from reduced packet dropping and latency. The method also improves the network throughput because the present excess traffic is not considered as an indication that more bandwidth be allocated at that instance. Thus, the disadvantage of this approach is its complexity and computational intensity; the implementation of trend analysis presupposes the use of rather complex algorithms and, constant monitoring of trends, which in turn are rather time-consuming and may involve considerable resources. Still the adaptive strategy can be termed to be a more effective method of combating congestion than the traditional congestion control method.

3.4 Design

Leandro et al [20] in 2024 proposed the DESiRED, a novel AQM approach, integrates DRL and In-band Network Telemetry (INT) in IoT environments to dynamically manage network congestion. Traditional AQM techniques like RED and its variants, lack adaptability to changing conditions. Advanced methods like CoDel, PIE, and machine learning-based AQMs offer improvements but still face limitations in dynamic IoT contexts. DESiRED's use of DRL for continuous learning and INT for real-time network insights significantly enhances performance metrics such as latency, packet loss, and throughput. However, the approach faces challenges like high computational and energy overheads, implementation complexity, and stability concerns. Future research to optimize DRL efficiency, reduce INT overhead, and improve system robustness and security.

Huihui et al [13] in 2021 propose a unique framework inspired by DRL and implement the DRL-AQM algorithm to solve the problem of model accuracy and parameter tuning , After training, the neural network may be put online and function effectively in many scenarios without the need for parameter tuning . Through DRL-AQM, the optimal dropping policy may be learned by the AQM. After being trained in a basic network scenario, DRL-AQM may identify complex patterns in the data traffic model and use this to enhance performance in a wide range of scenarios. In several intricate network circumstances, the outcomes of DRL-AQM algorithms surpass those of traditional AQM algorithms. It is resilient and unaffected by network conditions, maintaining a consistent low buffer capacity use without causing throughput degradation through over-dropping. And DRL-AQM adjusts to the network links dynamics automatically and continually. Selecting the appropriate hyper-parameters to train a neural network is a difficult and resource-intensive step in the algorithm training phase.

Minsu et al [21] in 2021 suggested the design of a DRL based AQM (DQN-AQ), taking into account the three factors of queuing latency, dequeue rate, and queue length to determine the state. Introduce scaling factor in our

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reward function to accomplish the trade-off between queuing delay and throughput, in order to handle the massive quantity of traffic generated by IoT devices and to minimize queuing delay. Deployed the AQM scheme at the fog/edge node interface that is linked to the cloud gateway. Simulated the scheme's performance and compared it to popular schemes including P-FIFO, RED, PIE, CoDel, and FQ-CoDel. The suggested DQN-based AQM scheme demonstrated reduced queuing latency in the majority of cases while maintaining above the average throughput in the stochastic IoT context. The drawbacks include high computational and data requirements, implementation complexity, and energy consumption. Balancing these factors is essential for the practical deployment of DRL-based AQM solutions in IoT networks.

Jianing et al [22] in 2022 proposes MACC (Multi-Agent Congestion Control) leverages DRL in a cross-layer framework to enhance congestion control in dynamic and heterogeneous networks in IoT environments. On the contrary traditional single-layer methods like TCP and AQM, which struggle with adaptability, MACC employs multiple DRL agents that operate at different network layers and locations, facilitating real-time adaptation and holistic network management. The cross-layer congestion control is done by two Agent implementing a Deep Q-learning model. This approach improves performance metrics such as throughput, latency, and packet loss. The framework faces challenges including high computational and implementation complexity, stability and convergence issues, and inter-agent coordination difficulties. Addressing these challenges through optimization and simplification is crucial for the widespread adoption and effectiveness of MACC in real-world scenarios.

Micha et al [23] in 2023 introduce the development and evaluation of QueuePilot, an RL-based AQM policy designed to optimize how well backbone routers' tiny buffers function, trading off high utilization low loss rate and quick latency. With QueuePilot, the early congestion notification (ECN) marking likelihood is automatically tunes. QueuePilot is implemented and trained on a genuine testbed network, running in real time with UDP background flows and hundreds of TCP connections. Where QueuePilot consistently demonstrates high performance, outperforming existing AQM algorithms in small buffers and perhaps exceeding their performance in larger buffers. The drawback of QueuePilot not take into account the equity among flows in the reward function, and devoid of performance guarantees.

Anuarbek et al [24] in 2023 proposed mapping-ECN as a solution to the incorrect marking issue. Where adjusting ECN marking thresholds in multi-queue Data Center Networks (DCNs) using deep learning offers a dynamic solution to the challenges of static threshold settings. The adaptability enhances overall network performance, reducing latency and packet loss while maintaining high throughput. Mapping-ECN begins prioritizing packets by evaluating the congestion percentage in the dual related port buffer, and preventing starvation by using the end host's aging mechanism. By leveraging deep learning, particularly neural networks, this approach can predict and adjust ECN thresholds in real-time based on continuous monitoring of network conditions. Mapping-ECN may transmit marked packets as quickly as conceivable by segregating marked and elephant packets while prioritizing marked and mice transmissions. If there isn't enough capacity in the buffer to transmit packets that exceed the buffer's threshold, mapping-ECN utilizes Cut Payload (CP), which removes packet payloads rather than metadata when a queue surpasses the threshold. Consequently, only one bit containing the packet's contents will be sent. As a result, the sender will instantly retransmit that packet without waiting for a timeout like TCP. The implementation requires substantial data for training, adds complexity to network management, and demands significant computational resources.

Hassan et al [25] in 2021 based on Weighted Fair Queuing (WFQ) proposes a Deep Q-learning Network (DQN) for optimal weight selection in an AQM system. Designed a DQN-WFQ algorithm that uses deep Q-learning to enhance taking decisions in a smart queuing method, and implemented a DQN-WFQ agent that learns the best weights for classifying several types of networks flows: gold, silver, and bronze. Every of these classes provides a set of throughput and latency requirements, and the neural network uses deep reinforcement learning methods like targets and replays buffers to learn the optimum weights based on network state. Goal is to improving decision-making while enhance quality of service (QoS). The DQN-WFQ algorithm has the capacity to adjust to flow needs and provide shorter latency compared to traditional WFQ, demonstrates the capability of the DQN agent to continuously learn and update weights to maximize rewards, meeting throughput and delay requirements for different classes of network flows. However, the implementation of the DQN-WFQ algorithm may introduce additional overhead and complexity to the network management system. Which may require training time and significant computational resources.

KEFAN et al [26] in 2019 proposes TCP-Drinc, a model-free, intelligent congestion management method based on DRL. It uses prior experience in the shape of a collection of measurable characteristics to determine how to alter the window of congestion size. The technique does not need accurate models for network, scheduling, or network traffic flows, does not require data for training, and is resilient to changing network circumstances. The

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TCP-Drinc system also provides excellent solutions to various long-standing congestion control concerns, including delayed environment, incomplete apparent information, and measurement variances. The study mainly focusses on their performance on throughput and RTT. TCP-Drinc uses a deep convolutional neural network (DCNN) combined with a long short-term memory (LSTM) network for learning from previous data and choose the next action to alter the window of congestion size. ns-3 were used for comprehensive simulation and comparison with, TCP NewReno, TCP-Cubic, TCP-Hybla, TCP-Vegas, and TCP-Illinois, where it showed superior performance. One of the challenges highlighted in the study is the instability problem of the training process. Where the authors proposed two strategies: experience replay and target networks.

Yifei et al [27] in 2021 propose a new ECN marking scheme (MM-ECN) to DCTCP. Describe the standard ECN marking strategy for DCTCP. Identify this scheme as TM-ECN. Through simulation. It was revealed that TM-ECN has poor queue stability, burst tolerance, and short-flow friendliness. FM-ECN and RM-ECN were created to address these problems. FM-ECN has the highest burst protection and queue stability, whereas RM ECN is the best for short-flow friendliness. However, neither FM-ECN nor RM-ECN can give optimal burst resilience and short-flow friendliness concurrently. Implemented ECN marking techniques in the Linux kernel and ns-3 for evaluation. Large-scale simulations reveal that MM-ECN provides almost optimal control of burst tolerant and short-flow friendliness. The MM-ECN also manages queue stability better than the RM-ECN. That developing and implementing dynamic algorithms to determine the optimal marking position can be highly complex, significant computational overhead, requires extensive data collection and processing.

3.5 Survey

Amir et al [28] in 2020 Comprehensive survey explores the various techniques, strategies, and technologies developed to enhance network performance, focusing on both latency (time delay in data transmission) and throughput (amount of data transmitted over time). Where include understanding fundamental concepts of latency and throughput, exploring network architectures such as wired, wireless, and hybrid networks, and examining hardware advancements and high-speed routers. Where Software techniques, including protocol optimizations and traffic management, are discussed alongside emerging technologies like 5G networks, IoT, and edge computing. It's also presenting case studies of real-world implementations and a comparative analysis of different optimization techniques. Challenges such as scalability and security concerns are addressed, with future research directions highlighting the potential integration of AI and machine learning. The survey concludes that optimizing latency and throughput is complex but essential, necessitating continuous research and development to meet growing demands for faster and more reliable network performance.

Josip et al [29] in 2021 The survey addresses the performance of TCP congestion control (CC) algorithms in the context of 5G mobile networks. Discusses the challenges to TCP CC, including blockage issues, beam misalignment, handovers, inadequate buffer sizes, interference from non-data signals, and data flow changes due to edge computing. Highlights the potential for machine learning (ML) techniques to enhance TCP CC performance. Previous research has assessed the performance of TCP CC algorithms in 5G, identifying limitations and suggesting enhancements such as edge computing and modified congestion detection mechanisms. ML-based algorithms, capable of learning and adapting to complex network conditions, are seen as promising candidates for future TCP CC implementations in 5G and beyond.

4. Distribution by Simulation

Figure 3 demonstrates the number of papers categorized by simulation use. Nearly 9 papers used NS-3. Only 3 articles used NS-2. Two used Linux kernel. Two used realistic, one cooja simulation, slotted ALOHA AND CSMA/CA USE one, and three articles did not use simulations.

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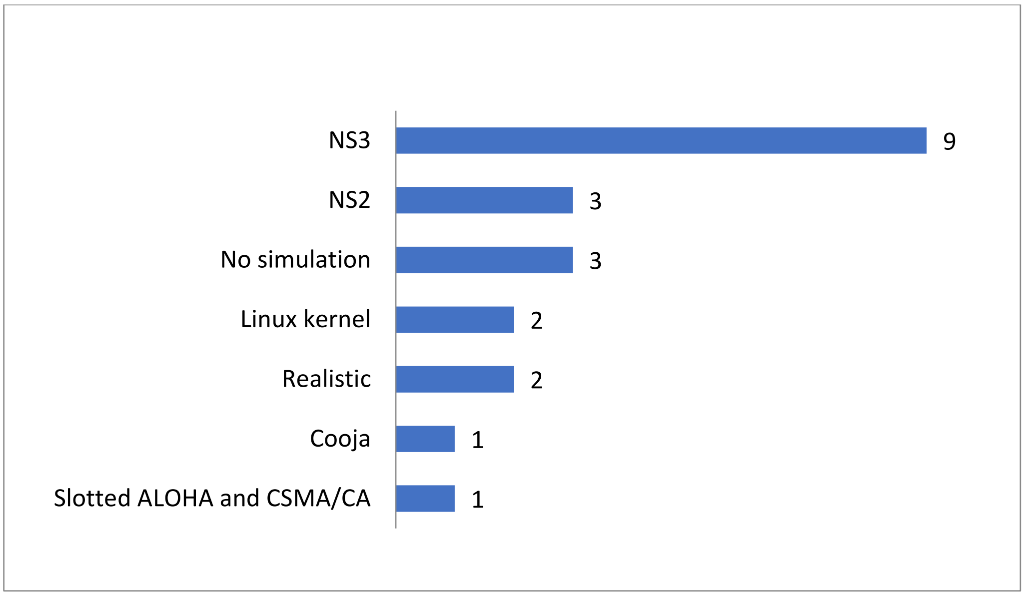

Figure 3. Number of included articles based on the type of simulation used

4.1 Distribution by the publication years

Figure 4 shows the number of articles included in (5) categories, namely, development, evaluation, analysis, and review by publication year. This figure presents the number of scholarly papers distribution during the period of 2019 to 2024.

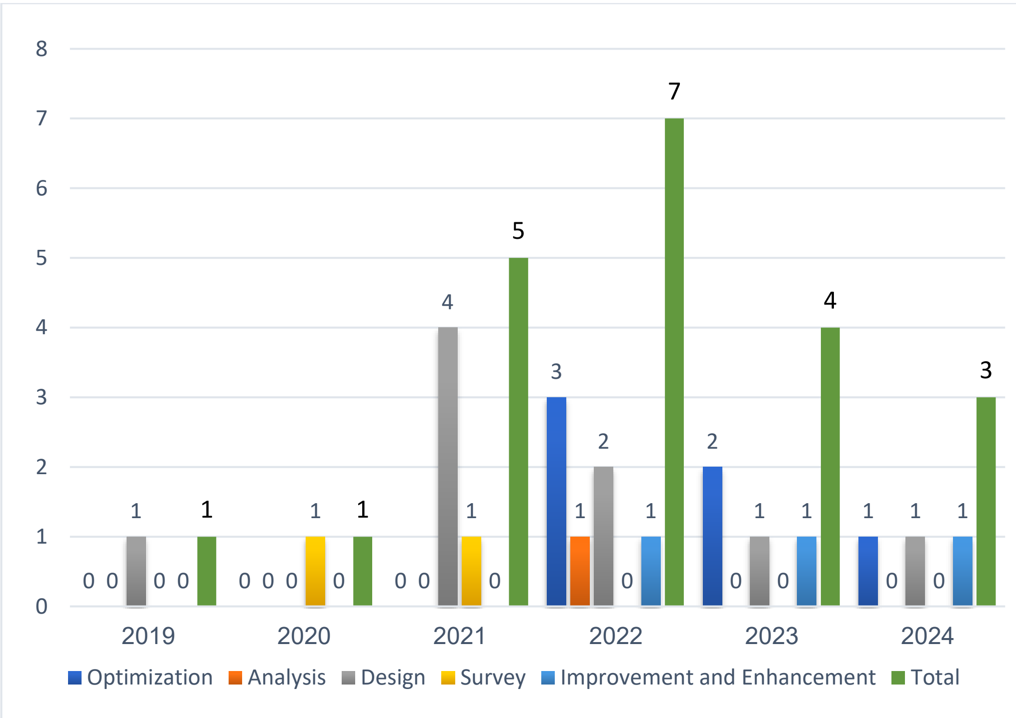

Figure 2. Number of inclusive articles in different grouping depends on the year of publication

Nearly 7 articles have been issued during 2022. A total of 5 papers were published in 2021. A total of 4 articles were issued in 2023. Three papers were published in 2024, and 1 paper were published in 2020, 2021 respectively.

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Table 1: Selective research papers

Author(s) / Year. Ref	Simulation	Problems	Advantage	Motivation	Challenges	Aim Of	compares to
Jing et al. 2022 [30]	NS-2	Not ability to efficiently manage network queues and reduce congestion in modern, complex network environments.	The QP-AQM algorithm enhances congestion management, throughput, latency, traffic prediction accuracy, and reduces packet loss.	To improve upon these traditional AQM algorithms by incorporating machine learning, specifically Q-Learning, to predict network traffic patterns and proactively manage queue lengths.	The QP-AQM algorithm addresses network complexity, high traffic, dynamic patterns, latency, throughput, and parameter sensitivity.	The goal is to reduce congestion and packet loss while meeting the increasing demands for low-latency and high-throughput network performance.	ARED and RED to QP-AQM
Aya et al. 2022 [14]	NS3	the effect of changing the bottleneck link bandwidth and bottleneck latency	The advantages are adaptive Parameter Tuning, Improved Performance, Scalability, Automation and Robustness.	The study aims to develop a smarter AQM algorithm to reduce network delay more effectively than traditional methods.	The study aims to develop an AQM algorithm that adapts, reduces latency, improves throughput, and ensures fairness.	Evaluate a deep reinforcement learning-based AQM algorithm by comparing DQN-QM and RED on latency, throughput, bandwidth, latency, and training data size.	RED to DQN-Q
Taewon et al . 2024 [15]	slotted ALOHA and CSMA /CA	Managing CH's queue condition is crucial in order to extend the network's lifespan or satisfy Quality-of-Service (QoS) requirements.		Improving Information Freshness (AoI), Enhancing Energy Efficiency, Addressing Network Congestion and Dynamic Adaptation to Network Conditions	The challenge of design a framework that can efficiently balance AoI and energy consumption while adapting to dynamic and resource-constrained environments.	The study aims to enhance the efficiency, reliability, and sustainability of IoT sensor networks, making them more effective for a wide range of applications.	SRED, CoDel to DeepAAQM
Praveen e t al . 2023 [16]	cooja simulator	The issue pertains to the effective management of network congestion in IoT environments utilizing Constrained Application Protocol (CoAP).	The study offers adaptive control, enhanced resource utilization, improved network performance, and better Quality of Service (QoS).	iCoCoA is motivated by the need to address IoT network challenges, including dynamic conditions, resource constraints, and varied application requirements.		The aim of the study is to develop an intelligent and adaptive congestion control algorithm for CoAP-based IoT networks that leverages deep reinforcement learning.	CoAP, CoCoA, and CoCoA+

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Prohim et al . 2022 [17]	NS-3	Large-scale heterogeneous IoT cellular networks face challenges such as massive multi-dimensional model update iterations and resource-constrained computation.	the study's advantage lies in its potential to significantly improve the efficiency, scalability, and adaptability of federated learning in software-defined IoT environments	The study of Multi-Agent Deep Q-Networks (MADQNs) for edge federated learning (eFL) in SD-IoT aims to manage IoT device heterogeneity, improve computation offloading, reduce frequent model updates, and enhance QoS.	The research addresses IoT device heterogeneity, communication overhead and delay, ensuring high QoS for important missions, and using SDN and NFV technologies.	The research seeks to increase resource automation, optimize edge resource consumption, improve global QoS, and provide a versatile solution for dynamic IoT networks.	MRES, SADQN, to MADQNs
Shahzad et al. 2023 [18]	the Mininet emulator and the Linux kernel	Traditional networking often fails to manage congestion optimally due to undefined ECN threshold values.	RLECN provides dynamic adaptation, optimized resource use, improved QoS, scalability, automated ECN adjustment, and compatibility.	RLECN aims to tackle modern networking challenges, including complexity, high traffic volumes, diverse patterns, and the need for scalable congestion management.	The study challenges optimizing the ECN threshold in routers, lacking a universally optimal value for improving network performance under varying conditions.	The RLECN study aims to improve network performance and QoS using RL and SDN for adaptive, scalable operation.	FQ-CoDel and Intelligent AQM to RLECN
Ayman et al. 2022 [3]	NS-3	Congestion control to manage the increasing volume of network traffic while minimizing congestion, packet loss, and latency.	The system leverages deep reinforcement learning to automatically adjust AQM parameters, enhancing network efficiency, performance, and congestion management adaptability	The goal is to develop adaptive algorithms using deep reinforcement learning to enhance network efficiency, performance, and congestion management amid rising traffic and traditional control limitations.	The challenge is managing congestion with rising traffic and dynamic patterns, requiring adaptive solutions to optimize performance beyond traditional methods.	The aim is to develop a deep reinforcement learning-based congestion control algorithm to enhance performance, automate parameter adaptation, and surpass traditional methods.	RED to DQN
Majid et al. 2023 [31]	NS-3	Managing network congestion, throughput, delay, and packet loss ratio.	Handling high-traffic loads, reducing network congestion, and preventing packet loss, even under high-stress conditions.	The motivation is to enhance network stability and congestion control using an ensemble of four DRL models for high throughput, low delay, and minimal packet loss.	Optimizing network stability and performance with high traffic and dynamic conditions by integrating four DRL models with different action spaces.	The aim to develop and evaluate a weighted ensemble Deep Reinforcement Learning (DRL) model for congestion control in Transmission Control Protocol/Internet Protocol (TCP/IP) networks.	RED, DQN, DDPG, PPO, TD3

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Ayman et al. 2022 [2]	NS-3	Network Congestion and Packet Loss	DQN offers dynamic adaptation, reduced packet loss and delay, scalability, and potential for further improvement.	DQN addresses limitations of traditional congestion control, meeting the needs of modern, dynamic networks with enhanced adaptability and efficiency.	Implementing DQN for network management involves addressing challenges like dynamic environments, training instability, exploration-exploitation tradeoffs, scalability, and safety.	DQN aims to mitigate congestion, enhance performance, and adapt to dynamic conditions in network management using advanced machine learning techniques.	RED to DQN
Chengsheng et al . 2024 [19]	NS-2	The problem of study is Network Congestion and Queue Length Management.	The study benefits include dynamic operation, performance boost, and quality of service, simplicity, scalability, and reliability.	The study addresses dynamic network conditions, improving performance and quality of service with new, anticipative technologies.	The three issues are: Dynamic Network Conditions, Accurate Queue Length Measurement, Complexity of Adaptive Algorithms	The purpose of the study is to design and assess the new congestion control algorithm for congestion that current techniques fails to solve.	AQM algorithm to AQMRD
Leandro et al. 2024 [20]	realistic	AQM algorithms use fixed thresholds, such as target delay or queue occupancy, to determine when to drop packets to prevent congestion.	Dynamic adaptation, improved QoS, reduced packet loss and delays, DRL integration, scalability, flexibility, and leveraging in-band network telemetry (INT).	The motivation for this study Dynamic Nature of Network Traffic, Impact on Quality of Service (QoS), Advances in Network Telemetry and Machine Learning and Need for Programmable and Adaptive Solutions.	The study addresses challenges including network dynamics complexity, precise telemetry data, generalization, training DRL models, and infrastructure integration.	The study aims to advance AQM techniques with a dynamic, adaptive solution to manage buffer congestion and enhance user experience.	iRED to DESiRED
Huihui et al. 2021 [32]	NS-3	The problem addressed Network Congestion Due to Bursty Traffic and Buffer Size and Bufferbloat.	DRL-AQM adapts to changing conditions, reduces packet drops, maintains stable queues, and uses buffer capacity efficiently in real-time.	Develop a DRL-based AQM algorithm to optimize packet dropping, reduce loss and delays, enhance throughput, and adapt to dynamic environments.	Complexity of Network Dynamics, Heterogeneous Traffic, Scalability and Performance, Real-Time Adaptation and Learning.	Enhance network efficiency by minimizing packet loss, minimizing latency, ensuring high throughput, optimizing buffer utilization, and adapting to dynamic environments.	RED to DRL-AQM

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Minsu et al . 2021 [21]	NS-3	The problem is managing high-volume, dynamic IoT traffic at fog/edge nodes, aiming to reduce queuing delays and maintain throughput.	The DRL-based AQM scheme improves delay, jitter, throughput, and scalability, offering superior IoT traffic management.	Proposing the DRL-AQM scheme addresses dynamic IoT traffic, meets latency and throughput needs, and overcomes existing AQM limitations with real-time adaptation.	Challenges include managing high IoT traffic, balancing throughput and delay, adapting to dynamic patterns, and ensuring scalability and stability.	The aim is to develop and validate a DRL-based AQM scheme to manage dynamic IoT traffic, optimizing delay, jitter, and throughput.	P-FIFO, RED, PIE , CoDel and FQ-CoDel to DRL-AQM
Jianing et al . 2022 [22]	NS-3	The challenge of efficiently managing congestion control in dynamic network environments.	The MACC framework offers improved coordination, adaptive control, higher throughput, and lower packet loss compared to traditional congestion control schemes.	The motivation for developing the Multi-Agent Congestion Control (MACC) framework from Complex Network Environments, Limitations of Existing Algorithms, Advancements in Machine Learning.	The challenges of MACC are, Dynamic Network Conditions, Cross-Layer Protocol Mismatch, Buffer-Bloat Problem, Quality of Service (QoS) Requirements.	Aiming to improve throughput, reduce delay, and utilize resources efficiently, especially as network traffic increases.	RED, CoDel and RL-QUE with NewReno, BBR, and RL-TCP to MACC.
Micha et al . 2023 [23]	NO	The problem is using small buffers in backbone routers while maintaining high network performance.	QueuePilot offers efficient small buffer utilization, low loss rates, short delays, consistent performance, and a lightweight policy.	To provide lower delays for users and free up capacity for vendors.	QueuePilot addresses challenges in small buffer management, balancing high utilization with low loss, ECN marking tuning, and complex traffic patterns.	Introduce QueuePilot, an RL (reinforcement learning) based AQM that enables small buffers in backbone routers, trading off high utilization with low loss rate and short delay.	Droptail Policy and Existing AQM Algorithms such as RED, PIE, CoDel to QueuePilot.
Anuarbek et al. 2023 [24]	NS-2	the wrong marking problem	Mapping-ECN improves network performance by reducing latency, managing congestion, and maintaining throughput through Cut Payload, ensuring fairness and adaptability.	Mapping-ECN addresses multi-queue challenges, wrong marking, latency, throughput, fairness, and dynamic conditions, improving congestion management in data centers.	Mapping-ECN addresses incorrect marking, distinguishes between short and long flows, maintains low latency, high throughput, and avoids repeated marking.	The study aims to develop and validate Mapping-ECN for multi-queue DCNs, ensuring low latency, high throughput, fairness, and robust performance.	MQ-ECN to Mapping-ECN

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Hassan et al. 2021 [25]	NS-3	The problem addressed Classified Network Flows, Throughput Requirements, Delay Sensitivity, and Traditional Approaches Limitations.	DQN-WFQ offers adaptability, optimization, prioritization, and robustness, improving performance for managing network flows with strict throughput and delay requirements.	Complex network traffic and traditional management limitations drive the need for adaptive solutions using deep reinforcement learning for dynamic adjustments.	Challenges include managing diverse traffic, dynamic network conditions, QoS requirements, security concerns, and balancing throughput with delay.	The aim is to develop a dynamic queue management algorithm to optimize resources, prioritize flows, and enhance QoS and network efficiency.	WFQ to DQN-WFQ
KEFAN et al. 2019 [26]	NS-3	The study tackles the problem of inefficient and static TCP congestion control mechanisms by introducing a deep reinforcement learning-based approach.	TCP-Drinc offers adaptability to dynamic conditions, enhanced robustness, scalability, learning from diverse traffic patterns, and improved congestion control.	The motivation behind the development of TCP-Drinc Limitations of Traditional TCP Congestion Control, Need for Higher Efficiency and Reliability, and Increased Network Complexity.	The challenges of study are Real-Time Adaptation and Decision Making, Reward Function Design, Scalability and Robustness.	TCP-Drinc aims to provide a more robust, efficient, and reliable solution for managing network congestion, ultimately improving the performance and quality of service in modern and future networks.	TCP-Cubic, TCP-Hybla, TCP-NewReno, TCP-Vegas, and TCP-Illinois to TCP-Drinc.
Yifei et al . 2021 [27]	Linux kernel and ns-3	Long ECN feedback delay, significant queue oscillation, and poor short-flow friendliness.	The schemes enhance network performance, reduce queue oscillation, improve resource utilization, and deliver faster flow completion and better user experience.	The study aims to improve TM-ECN limitations by developing ECN schemes that enhance delay, stability, flow handling, and network performance.	MM-ECN challenges include integrating with legacy systems, standardization, updating firmware, tuning for specific environments, and significant costs and ongoing evaluation.	The aim is to create more efficient and scalable congestion control mechanisms that meet the evolving demands of datacenter networks.	Traditional Tail Mark ECN, Front Mark ECN, Random Mark ECN (RM-ECN) to Mixed Mark ECN (MM-ECN).
Amir et al. 2020 [28]	NO	The survey provides a comprehensive examination of the various factors affecting latency and throughput in modern networks.	The study offers a comprehensive understanding of improving service quality, fostering innovation and research, and benchmarking performance measurement.	The motivation of meet increasing performance demands, utilize technological advancements, gain a competitive edge, achieve cost efficiency, ensure scalability, and meet QoS requirements.		The study analyzes latency and throughput optimization in modern networks, advancing understanding, guiding implementation, and identifying research gaps.	

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5. Discussion

The primary goal of this effort was to present an update on the RED mechanism research. The purpose of this study is to highlight current research trends in this area. Because the RED mechanism literature is the main emphasis of this study, it differs from earlier ones. Moreover, it arranges the associated research in a taxonomy. Based on a comprehensive literature review spanning 2019 to 2024, this study investigates AQM mechanisms, with a particular emphasis on enhancing the RED algorithm through DRL techniques for congestion control. Initially identifying 68 papers from prominent databases like Google Scholar, IEEE Explore, and Science Direct, the study rigorously selected 21 relevant articles that explored algorithmic innovations such as QP-AQM, DQN, DeepAAQM, iCoCoA, and RLECN. These advancements aim to tackle congestion challenges through adaptive learning and predictive capabilities. Comparative analyses consistently demonstrate that DRL-based approaches outperform traditional AQM methods like RED, showcasing improvements in latency, throughput, and overall network efficiency across dynamic network conditions. However, challenges such as computational complexity, stability concerns (e.g., RTT oscillations), and the need for extensive real-world validation remain significant. Utilizing simulation platforms like ns-3 and Linux kernel, researchers validated these algorithms, highlighting their practicality and scalability. Looking ahead, future research should focus on refining algorithms, simplifying implementation, and overcoming deployment obstacles to realize the full potential of DRL-based AQM in diverse networking environments.

6. Motivations

The motivation behind this study lies in the increasing application of DRL in the networking field, particularly in addressing congestion control. The study's goal is to organize the research background in accordance with the literature, explain researchers' reactions to evolving technologies, and identify the characteristics that are inherent in this dynamic field of research. This is why, based on an investigation of congestion management using the AQM mechanism depending on the RED mechanism, the study intends to establish the benefits and potential challenges of including DRL into congestion control algorithms. As a result, this study aims to contribute to the existing body of knowledge about the present status of managing congestion and AQM in networks by providing insights into the research methodology used, the observed findings, and the potential downsides of the chosen works.

7. Challenges

However, despite the discussed advantages, RED can is not a perfect solution for communication network delivery. The analysed articles showed that for the audience, the main problem is associated with certain difficulties in the mechanism of RED. The proposed AAQM system will be solving several crucial problem areas in network management mainly for high traffic volume and dynamism in the network [6]. Among the important issues, the potential of dynamic traffic, which implies more or less frequent operations at the same time, impacting the system's stability and optimal performance [28]. Another problem posed is that of buffer congestion and bursty traffic, which compounds problems of distribution by requiring the system to handle small floods of information as soon as potential packet drop is identified [24]. Lack of efficient packet dropping and its acceptability are two important concerns; that require the use of new methods to optimize the throughput and delay, and to minimize queuing delay [5]. The variability of networks' interactions, the heterogeneity of traffic, and the Size also challenge AAQM, as they require the continuous improvement of its models and the constant readjustment to the network's realities. Necessary challenges that have to be addressed by the DQN for network management includes issues concerning training instability, exploration and exploitation, and safety issues [16]. The system also has to overcome the current weakness of conventional congestion control in terms of righteous response to congestion, reliable fast and efficient cancellation of packet transmission while it must also include prognostication and tweaking parameter to bring out the ideal ECN marking [30]. Furthermore, system has to solve the buffer-bloat problem, the crossed-layer protocol incompatibilities, and QoS demands on the one hand and high link-utilization/low-loss-rate challenge on the other one as well as the fairness issue and complexity of interfering traffic patterns [23]. Consequently, the use of reinforcement learning algorithms is based on several problems, such as award function, scalability, and transferability of network environments [17].

8. Recommendation

The majority of the recommendations discussed in the literature review section point to the developed DQN algorithm's promising potential for dealing with network congestion control, as well as the algorithm's ability to improve network reliability, efficiency, and effectiveness [6]. The authors advocated doing more simulation and

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modeling research on the proposed DQN-WFQ approach and applying it to a range of network circumstances and configurations [28]. The proposed adjustments include fine-tuning the parameters and optimizing the function, as well as comparing the method to other current procedures. The use of DRL techniques for AQM is particularly recommended for IoT and fog/edge networks because of the option to scale the delay and the throughput via reward coefficients. As for the organization of the loops, the literature underlines the constant need for refinement and demanding energy efficiency, the inclusion of the multi-agent system is also proposed [24]. It is possible to apply the described approach to new cases and more generally, and extend it, for example, with the help of adding components connected to fuzzy logic in the future [5]. There is also a suggestion regarding the use of the transfer learning technology that envisions designing pre-trained models that will be only slightly tailored for new cases. Additionally, it is proposed to integrate the DRL-AQM in the Linux kernel and to configure a real testbed for the subsequent research, shift from offline to online training [14]. The study also focuses on coordination with key data centers for research as well as for trying out the findings and the deep learning algorithms with an aim of tweaking the dynamic thresholds as commonly seen in real life applications [27]. In the end, suggestions proposed are to experiment with transfer learning, improve the reward function, and guarantee the expressiveness and efficiency in larger Networks [23].

9. Limitations

First off, despite the fact that the sources used in this analysis are trustworthy and constitute thorough compilations, there is a pertinent constraint on the scope and nature of the database sources in this assessment. Second, because of the quick advancements in this field, the survey's timeliness is restricted. Thirdly, describing RED research activity may not always represent the actual usage of apps or their consequences. The goal of this analysis is represented by these work findings, which show how the research community has responded to the current developments.

10. Conclusion

In conclusion, the escalating demands and complexities of modern networks have intensified the urgency of effective congestion control mechanisms. Where study and research of queue management continues to be an active area for the researchers. This review reviews into the realm of AQM with a focus on the RED algorithm, motivated by to ensure optimal network performance amidst increasing traffic loads. Therefore, this review, which provides an analysis of the current literature, aims to highlight the trends and challenges that characterize the subject at this time. To this goal, research papers were obtained via database searches and subsequent screening processes. These assessments address a variety of topics, including planned upgrades to boost RED throughput, proposals to develop new AQM schemes, and the incorporation of new technologies like DRL for congestion control. The taxonomy used in this analysis spans all levels of research efforts and emphasizes the complexity of congestion management solutions in network systems. The review of the literature indicates that researchers are continuously improving RED to improve its functioning at network level and tackling the issues related with congestion control mechanisms.

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