A Review of TCP Congestion Control Using Artificial Intelligence in 4G and 5G Networks

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Abstract

In recent years, the field of research around the congestion problem of 4G and 5G networks has grown, especially those based on artificial intelligence (AI). Although 4G with LTE is seen as a mature technology, there is a continuous improvement in the infrastructure that led to the emergence of 5G networks. As a result of the large services provided in industries, Internet of Things (IoT) applications and smart cities, which have a large amount of exchanged data, a large number of connected devices per area, and high data rates, have brought their own problems and challenges, especially the problem of congestion. In this context, artificial intelligence (AI) models can be considered as one of the main techniques that can be used to solve network congestion problems. Since AI technologies are able to extract relevant features from data and deal with huge amounts of data, the integration of communication networks with AI to solve the congestion problem appears promising, and the research requires exploration. This paper provides a review of how AI technologies can be used to solve the congestion problem in 4G and 5G networks. We examined previous studies addressing the problem of congestion in networks, such as congestion prediction, congestion control, congestion avoidance, and TCP development for congestion control. Finally, we discuss the future vision of using AI technologies in 4G and 5G networks to solve congestion problems and identify research issues that need further study.

Keywords: 5G; 4G; Congestion Control (CC); Artificial Intelligent (AI); Machine Learning (ML); Deep Learning (DL).

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1. Introduction

According to Cisco, global Internet traffic will increase, and by 2023, over two-thirds of the world's population will have access to the Internet, with wireless and mobile devices accounting for more than 66% of this traffic[1]. Due to the diversity of devices and applications, mobile (4G) and (5G) mobile communication systems will have to handle a large number of devices connected at base stations, increased traffic volume, and a variety of applications with different features and requirements, making network infrastructure management difficult [2]. Some data can be used as a solution to manage network infrastructures and deal with congestion. For example, analysis of data in traffic can be used to predict congestion [3], or the historical data in the physical layer that is exchanged between the user and the base station may be exploited to avoid congestion [4] by using AI techniques.

AI is a scientific field created in 1950 and is capable of solving many human tasks such as speech, image recognition, etc. AI is a general field that includes machine learning (ML) and deep learning (DL) [5]. However, traditional ML approaches are limited to process data in its original form [6]. In recent years, DL has outperformed traditional ML techniques in many research areas, such as computer vision and natural language processing [7]. Similar to many application areas, AI models, especially DL, can be used to solve congestion problems in 4G and 5G networks, such as congestion prediction and control, etc. This paper provides an overview of the use of AI to solve congestion issues in 4G and 5G environments.

In [8], Ahmed and his colleagues applied DL and reinforcement learning (RL) to address the congestion problem and resource allocation problem in wireless networks. Also discussed, several issues and limitations related to resource allocation, such as maximizing throughput, minimizing interference, and energy efficiency. In this review, we present a more general review of the different AI models used to solve the congestion problem in 4G and 5G networks.

Zhang and his colleagues [6] provide a comprehensive survey on the use of DL in wireless networks, specifically mobile networks and their potential applications, identifying the intersection between these areas. Although relevant to our work, Zhang and his colleagues had a more general focus, dealing with issues related to public wireless networks such as the Wireless Sensor Network (WSN), and analyzing their data. Network congestion has a direct impact on network performance in general and leads to a decrease in the quality of service.

According to Joseph and his colleagues [2] congestion causes a decrease in network productivity and a decrease in service quality. As the number of user's increases, the throughput decreases, and the delays increases due to congestion, which are important factors, especially in 4G and 5G networks.

Depending on the nature of the data collected, a variety of AI methods are applied to control the congestion in the network. This review in contrast to other research, it focuses only on the 4G and 5G congestion problem being addressed by AI. Highlights on using specific types of AI models for congestion control (CC) and to improve network performance through improve throughput and delay.

After collecting many research journals on congestion control in 4G and 5G networks, a number of articles were found for review and studies that do not focus on the use of AI techniques for congestion control, and were excluded. This paper is organized as follows: Section 2 includes descriptive TCP congestion control. An overview of the methodology adopted to guide this review is provided in Section 3. Section 4 provides an evaluation and future work for the paper. While the conclusion in Section 5.

2. TCP Congestion Control Mechanism

TCP (Transmission Control Protocol) is a dependable end-to-end communication protocol standard [9]. TCP is in charge of establishing and terminating connections, controlling flow, and managing congestion on untrusted networks. TCP provides a flow control mechanism to establish how much data the receiver can receive. The receiver uses the window size ($cwnd$) in the TCP, which represents the size of the buffer available to the receiver. This informs the sender of the maximum number of packets it is allowed to send [10]. The mechanism of TCP CC is to avoid network congestion.

Congestion occurs in the network when the sender is pumping data at a rate that exceeds the ability of the node or receiver to handle it. The delay of each packet passing through the buffer increases due to buffers in communication nodes that are used to prevent packet loss during packet flow, and this delay degrades network performance [11]. Thus, delays occur and there is an overall degradation in network throughput. The maximum network link bandwidth is referred to as the congestion bandwidth. No congestion occurs when the TCP data rate is less than the congestion bandwidth [10]. However, congestion occurs when the transmission rate exceeds the congestion bandwidth, causing the buffers to become full, causing packets to be lost in the network node. TCP CC is the process of preventing congestion and ensuring efficient use of the network. TCP CC is an important part of the TCP protocol.

The main principle of TCP CC is to prevent the sender from sending more than the network capacity and limit the available capacity. The standard TCP CC mechanism is based on the additive increase, multiplicative decrease (AIMD) algorithm, which includes four stages: slow start, congestion avoidance, fast retransmission, and fast recovery [12]. Slow start (SS), congestion avoidance (CA) phases are introduced earlier, followed by fast retransmission and fast recovery.

2.1. The Slow Start and Congestion Avoidance TCP Mechanism

Slow Start Is the first strategy that is employed at the start of data transmission by setting a cwnd to one maximum segment size (MSS) and doubling it for each received ACK; hence, the cwnd will grow exponentially[13]. In the SS phase, the receipt of every ACK means the correct packet to be received in the receiver [14]. The sender enter the CA phase and the slow start threshold (ssthresh) is set to (cwnd /2) when a packet is dropped [15]. To avoid the quick increase in cwnd that leads to network congestion, the CA phase starts increasing the cwnd by one MSS at each RTT linearly. In a network environment, packet loss and three duplicated ACKs can be utilized as indication of congestion. When a packet loss occurs during the CA phase, ssthresh is set to half of cwnd and cwnd is set to one and return to SS phase. The sender enters the fast

retransmit and quick recovery phase after receiving three repeated ACKs.

2.2. The Fast Retransmit and Fast Recovery TCP Mechanism

The general idea of these phases is to allow the sender to retransmit the lost segment even if the timeout has not expired. The Fast Retransmit starts when duplicate ACKs are received, which indicates a packet loss and the packet should be retransmitted. While the Fast Recovery algorithm occurs when it gets a three-duplicated ACK, it sets the *ssthresh* to 50% of *cwnd*. And *cwnd* is set to be the threshold plus three times the MSS. Whenever another duplicate ACK is received and a timeout occurs, the *ssthresh* is set to half of *cwnd*, and *cwnd* will be set by one MSS and return to slow start SS where ($cwnd = cwnd + MSS$). The fast recovery mode remains until it receives a new ACK, then it sets the *cwnd* to *ssthresh* and enters a congestion avoidance phase[14]. When a timeout happens in any of the TCP stages, it indicates packet loss, and the cwnd size is dropped to one MSS, and the ssthresh is decreased to half of the cwnd or twice the MSS. The slow start is then restarted, and the same scenario is repeated [16]. TCP CC algorithms are divided into three groups [10], as illustrated in Table 1:

Table 1: TCP CC indicators algorithms groups.

TCP CC algorithm group	Description
Loss based	Which utilize packet loss as a congestion indicator.
Delay based	Which determine packet loss using RTT measures.
Hybrid based	That combine loss-based and delay-based strategies.

3. Congestion control based Artificial intelligence (AI)

TCP (AI is an important branch in the period of big data. AI was born in 1950 and has made encouraging progress, particularly in ML, data mining, intelligent systems, robotics, and related applications[5]. AI includes ML and DL, which have many structures: Deep Neural Network (DNN), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Generative Adversarial Network (GAN), as they have been developed and applied in a wide range of sectors, including mobile networks. Recently, the leading areas of research have been in 4G and 5G networks, especially in predicting network congestion[17]. Congestion occurs as a result of network infrastructure bottlenecks that do not meet peak user demand. The task of forecasting congestion is to predict the variables at the time of the occurrence of congestion.

The most common indicators of congestion are packet loss and delay. Some papers predict congestion by loss. It should be noted that some of the papers included in this section predict congestion based on the delay indicator. Some papers predict the congestion based on the parameters of the physical layer. For each paper included here, we have indicated the indicator used for congestion, the layer used to control congestion, the type of network, and the improvement in network performance. The papers discussed in this section are summarized in Table 2.

In[18], the authors used ML algorithms to estimate network time (RTT) in congested networks to predict network performance. Weights are updated after each RTT measurement based on the difference between the estimated and actual RTT. The simulation results showed that the proposed ML algorithm adapts very quickly to

RTT changes, shows a significant decrease in packet retransmission and an increase in throughput in congested networks, and achieves a 40% improvement over standard TCP protocols.

Lu and his colleagues [19], developed a cross-layer technique named CQIC that uses physical layer information, such as the Channel Quality Index (CQI) and Discontinuous Transmission Ratio (DTX), to find the available bandwidth in evolved high-speed packet-access (HSPA+) networks. It also eliminates the slow-start phase, allowing users to take advantage of available bandwidth right away. When the RTT is comparable, the CQIC algorithm can outperform the Cubic algorithm in terms of throughput. The throughput performance is the same while sending large files, but the CQIC reduces the overall RTT by 2.38—2.65 times.

The authors in this article [20], proposed a supervised deep neural network system and appropriate input/output characterizations of heterogeneous network traffic. The proposed DL model has many hidden layers. Each hidden layer is used to compute a non-linear transformation of the previous layer. Thus, the DL model can predict more complex functions. The results showed that the DL system can improve heterogeneous network traffic control compared to a benchmark routing strategy (Open Shortest Path First (OSPF)) in terms of significantly better signaling overhead, throughput, and delay.

In [21], the researchers used ML represented by proposed Q-learning based RL in TCP cwnd adaptation during a congestion avoidance state, where the traditional window alternation is replaced, allowing the protocol to respond immediately to previously observed network conditions. The simulation result showed that the learning approach improved the throughput by 33.8% and 12.1% in delay.

In 2019, Huang [4] focused on utilizing the physical layer network information in LTE radio networks in order to avoid congestion, which had an influence on network congestion. She then used these datasets to train a DL method to avoid congestion using LSTM and MLP algorithms and to improve user throughput and utilize available capacity as much as possible. She discovered that the LSTM has higher throughput than both BBR and DCTCP with L4S, but also has a longer delay. MLP did not demonstrate any progress.

Other authors [22] propose a deep learning-based TCP (DL-TCP) for congestion avoidance in 5G mm-Wave network. DL-TCP can learn about node mobility and signal strength, and then change the TCP sending rate based on the network's disconnection and reconnection. Researchers have demonstrated that the DL-TCP can give more throughput and stability than today's TCP New Reno, TCP BBR, and TCP Cubic.

Sander and his colleagues [23] use a DL method for recognizing congestion variants in wireless networks based on packet arrival times. They built deep learning-based Passive Congestion Control Identification (PCCI) for CQIC to be easily adaptable to new TCP congestion control variants. When compared to traditional TCP congestion control like BBR, they demonstrated that it can effectively distinguish congestion variants. However, when there aren't enough distinguishing factors, the method fails to identify loss-based congestion control.

Ohzeki and his colleagues [24] demonstrated the capability of the DL method to forecast congestion control algorithms in wireless networks. They explained in the study that the sending rate can be estimated based on the information collected from the sends/receives packet trace, including both data segments and ACK segments

and MSS, to estimate cwnd values during RTT intervals. The results indicate that the LSTM algorithm can identify many congestion control techniques with similar features, including TCP Reno, CUBIC, and BBR.

Han and his colleagues [25] in 2019, developed a ML model to increase TCP performance in congested wireless networks. The MLP method was employed to distinguish the packet losses due to congestion from losses due to channel error in the network. The method has 98% accuracy in packet loss classifications in wireless environments and provides a large throughput when compared to current congestion controls such as TCP Veno, TCP Reno, and TCP Westwood+.

In 2020, M. R. Kanagarathinam and his colleagues [26] established and analyzed Dynamic TCP (D-TCP) in the 5G NR and LTE-A networks to assess available channel bandwidth and utilize it to derive the N congestion control factor in order to adaptively increase or decrease cwnd. The researcher provides and analyses the performance of the D-TCP algorithm in both networks using the NS3-mmWave and NS3 LTE-A simulators, respectively. The simulation results of D-TCP provide good results when compared to different TCP congestion control algorithms, such as TCP Reno and TCP Cube. It obtained a 32.9% and a 124.92% increase in throughput, respectively.

In this study[27], a proactive wake-up scheme is proposed in 5G networks based on the LSTM traffic prediction model. The effectiveness of the proactive scheme was examined through the prediction of user traffic. The simulation results, which used different types of data traffic, indicate that the proactive scheduler consumes less power than the unscheduled wake-up method.

In addition to a growing number of articles are being published that survey recent work that incorporates DL into the field of 4G and 5G networking. In [28, 29] address numerous issues that are facing the 5G networks, including congestion, and propose strategies to address these issues by applying AI to network architecture, as well as novel concepts for its use to achieve optimal performance and improve service quality.

To build effective congestion control algorithms in the transport layer, some researchers [30, 31] introduced metrics that can be exploited from the transport layer to solve congestion control problems and improve the performance of the 5G network and beyond, such as delay and its association with congestion.

Some of these studies [32, 33] provided a comprehensive overview and comparison of DL applications based on current in end-to-end networks that rely on high-frequency networks and short delays such as 5G network. They concentrated on several RL-based congestion control methods, which outperform standard CC algorithms. Fadlullah and his colleagues [34] recently published a survey on the progress of DL in a variety of wireless network fields, with a focus on its potential application in network traffic control systems. Their paper also identifies a number of unresolved research issues that should be investigated further in the future.

A survey on recent DL algorithms for Internet of Things (IoT) data analytics are discussed by Mohammadi and his colleagues [35]. They provide a thorough overview of present DL efforts in the IoT area, as well as current research difficulties and future directions. In wireless networking, Mao and his colleagues [36] focus on DL. Their research survey state of the art DL applications in wireless networks and explores future research

difficulties.

Table 2: summarizing the papers discussed in Section 3 (congestion control based AI).

Year	Ref	Congestion Indicator	Technique	Scope	Data source	Network improvement
2014	[18]	Delay based	ML	Wireless network	From simulator	Improve network performance by 40% through reduction in packet retransmission and an increase in throughput.
2015	[19]	CQI, DTX	ML	Wireless network	Public	Improve the throughput and reduces the overall RTT by 2.38—2.65 times.
2016	[20]	Hybrid	DL	Wireless network	From simulator	Improve network performance in term of overhead, throughput, and delay.
2016	[21]	Hybrid	ML(Q-Learning based on RL)	IOT	From simulator	Improved the throughput by 33.8% and 12.1% in delay.
2017	[34]	-	DL	Wireless network	public	It focuses on the few works that make use of DL applications for various network traffic control aspects.
2018	[35]	-	ML, DL	IOT	from network	It provides an overview of using ML techniques, especially DL, to facilitate analytics and learning in the IoT domain.
2018	[36]	-	DL	Wireless network	from network	This article covers some promising wireless applications and provides a list of solutions for ten research issues.
2019	[4]	4G radio parameters	DL(LSTM, MLP)	LTE	From simulator	improve overall performance on LTE network
2019	[24]	Loss based	DL(LSTM)	Wireless Network	Public	Distinguish ten congestion control algorithms
2019	[25]	Loss based	DL (MLP)	Wireless Network	Public	Improve the throughput by 98%
2019	[22]	Loss base	DL- TCP	5G	From simulator	Improve throughput and stability
2019	[23]	Loss base	DL(DeePCCI, LSTM)	Wireless Network	From simulator	can easily adapted for new congestion control variants

2019	[27, 28]	Hybrid	AI	5G	Public	Suggest new ideas for obtaining optimal performance and improving the quality of service.
2020	[29, 30]	Hybrid	AI, ML	5G	From network	Present research problems, methodologies, and recent results
2020	[26]	Loss base	DL(DynamicTCP)	5G NR, LTE-A	From simulator	D-TCP achieves 32.9% and 124.92% gain in throughput
2020	[27]	Hybrid	ML	5G	From simulator	Enhance the energy-efficiency of 5G mobile devices and reducing the buffering delay.
2021	[31, 32]	Hybrid	DL,RL	5G	Public	Provide a summary of how to use DL and RL to improve performance.

4. Evolution and Future Work

Research that solves the congestion of communication networks for the 4G and 5G networks is increasing. The complexity of their architecture and the increase in the volume of data and user devices present a major challenge to controlling the congestion problem. Several techniques have been developed for congestion control, and one promising direction to address this challenge is to adapt AI to control network congestion by preventing congestion before it occurs or eliminating congestion after it occurs based on congestion indicators such as packet loss and RTT.

Most studies have used congestion indices (packet loss and delay) to train the AI algorithms in order to control congestion. Although congestion indicators cannot prove network congestion because packet loss or delays are possible due to wireless network errors, frequent changes in these indicators make the process of congestion control complicated[25].

The DL has particular strengths for handling wireless networks, especially 4G and 5G networks, such as automatically extracting high-level features through layers of different depths, efficiently making use of huge amounts of mobile data generated at high rates; multi-tasking learning due to it containing two or more hidden layers and appropriate neurons that enable it to apply different tasks; and the DL is effective in processing classified or unclassified data, which is very important in dealing with large amounts of data as in the mobile phone system[6].

Data collection is an important factor in network congestion studies. Therefore, congestion indicators alone cannot be relied upon to control congestion. Rather, it can take advantage of the parameters available in the network layers to detect and control congestion.

The Cross-layer design is a promising technique for congestion control and enhancing the performance of the 4G and 5G networks. As in figure 1, the layer information available across layers, such as the physical layer and

the MAC layer, can collect a lot of information such as system parameters and radio parameters such as cell throughput, Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), Received Signal Strength Indicator (RSSI), Channel Quality Index (CQI), etc., which could enable a lot of intelligent higher level processes in terms of congestion control. This could optimize the congestion window ($cwnd$) in the transport layer based on the layer information that has an influence on the throughput and delay and thus improve network performance. Some studies used data from network layers to infer network bandwidth, which can be used to adjust the $cwnd$ and congestion control according to congestion rules [4].

The transport layer and physical layer information available during the transmission of data between the sender and receiver play an important role in congestion control. Two study focused on this information and looked at the contribution of this information to controlling congestion [4,19], and six looked at indicators of congestion [18, 23, 24, 21, 22, 25].
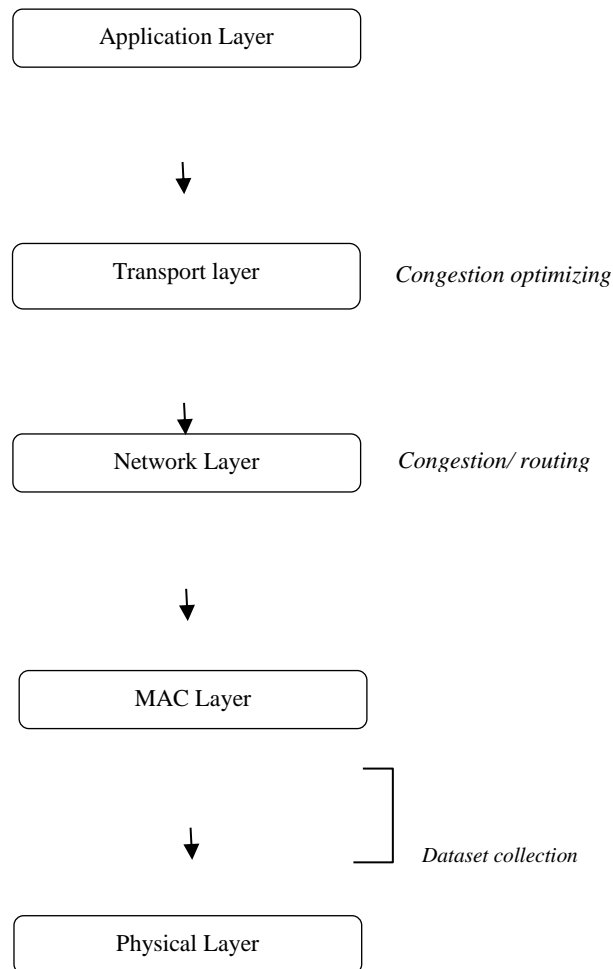

Figure 1: the cross Layer approach in the network.

Dealing with packet loss is a challenge in network throughput. Some have excluded their use and focused on the RTT indicator of the transport layer involved [18]. Others have implemented hybrid indicators that take

advantage of both packet loss and RTT for congestion control [20, 4,27, 28, 29,30,31,32].

Variables available across layers, such as radio parameters and physical layer information, can be a useful search scope in communication networks that require exploration as they are related to network throughput and can be used by AI algorithms to predict congestion before it occurs and avoid its consequences by adjusting the congestion window at the transport layer and maintaining higher throughput and a congestion-safe network.

However, depending on the congestion indicators used, different types of AI have been applied in different studies. Figure 2 shows the main branches of AI discussed in this article. But research is lacking to address the use of hybrid types of ML and AI together. Combining DL models such as LSTM and reinforcement learning (RL) is a good area of research. As such, DL has the potential to improve network performance and congestion prediction based on physical layer data, while RL can be used to change transmission rate based on latency.
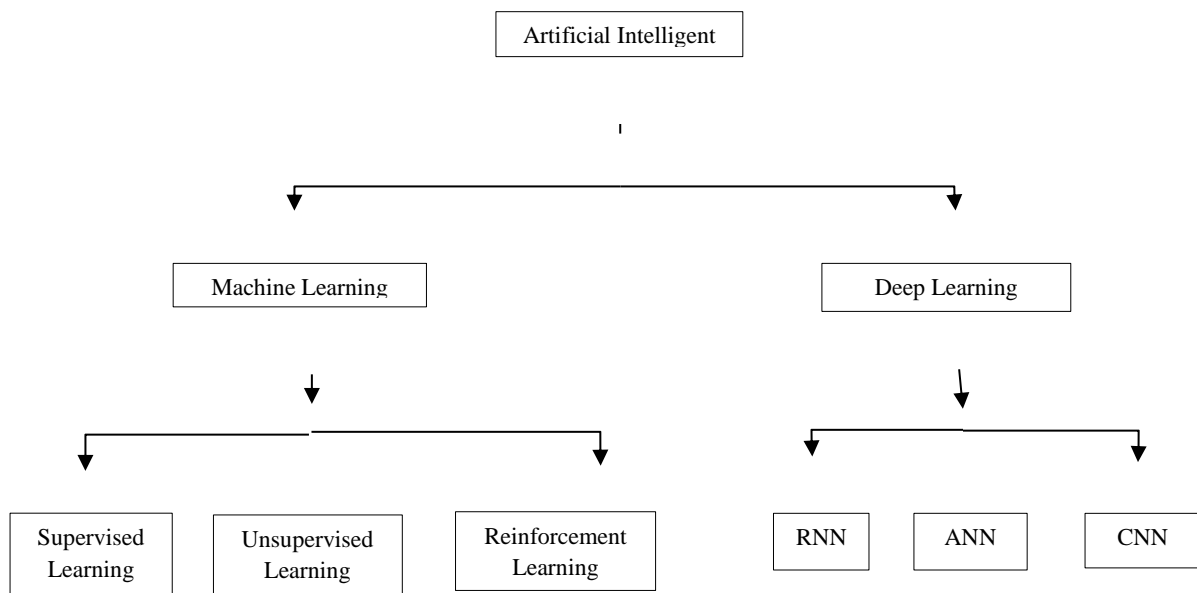

Figure 2: artificial intelligence branches in this article.

Over time, AI algorithms, especially DL models, have been developed, and their implementation has increased in wireless networks, especially 4G and 5G networks, to control congestion based on packet loss or RTT indicators, or both. ANN and RNN are the most widely applied models, while LSTM and MLP are the most commonly used algorithms in this class of algorithms. Most of the studies used LSTM models based on loss and delay, and only one study [4] used DL models based on transport and physical layer information to predict network congestion and improve throughput and delay.

Among all the DL models, RNN is the most suitable for congestion prediction. In some studies, the RNN performed better than the ML due to the parameters' selection [4]. Due to the lack of research in the field of using information layers in 4G and 5G networks by AI techniques to control network congestion, many new AI

algorithms have not yet been used. Table 3 summarizes the strengths and weaknesses of DL models in congestion control.

Table 3: Advantages and disadvantages of DL types.

DL Type	Advantages	Disadvantages
R N N	• n the processing of sequential data flow, it performs excellently. • ffective at classifying sequences. • rocesses time series with lengthy intervals and postponements efficiently.	• ong-term dependency has a negative impact on performance. • here is no firm guideline for dependency removal available.
A N N	• eeds less statistical training. • t has access to multiple training algorithms. • t has the capability of detecting complex relationships between dependent and independent variables.	• raining time increases with a large neural network. • uality predictions are less accurate as they need a large amount of data. • t has a greater computational cost. • t tends to overfit.
C N N	• eatures can be extracted automatically. • t takes less time to classify things. • apable of extracting characteristics from local connections and assembling them into high-level structures.	• t will be necessary to use a vast dataset. • t is necessary to turn traffic data into an image. • n CNN model depth and parameter selection, there are no known strategies.

DL models, especially LSTM type, showed better results than ML for controlling network congestion and had good accuracy in improving network throughput based on congestion indicators (losses and delays) in TCP traffic. All of the congestion control studies discussed in this article that apply AI techniques have shown

promising results. At the same time, there is no obvious delay improvement in a real-time congested network by relying on information from layers alone. Therefore, AI models that use the information layer to predict congestion and avoid its consequences with lower latency require research and exploration to be more effective in upcoming studies.

5. Conclusions

Congestion prediction and control in 4G and 5G networks have received more attention in the past few decades. With the development of network infrastructure and the increase in network demand, all communication networks face the problem of congestion. Therefore, forecasting and controlling congestion leads to better quality of service through improved throughput and delays. The combination of AI development and the availability of large data sets has led researchers to apply different models in this field. Although control models are generally simple and rule-based, control methodologies become complex when various factors affecting congestion are taken into account, such as radio parameters and various system parameters. Therefore, AI algorithms, especially DL, are becoming more and more popular over time as they can evaluate a large set of data. However, there is still a need to apply a wide range of different types of algorithms. Therefore, there is still an opportunity for researchers in the field of congestion control.

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6. Conflict of Interest

The author declares that she has no conflict of interest.

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