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Deep learning-based TCP congestion control algorithm for disaster 5G environment

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Abstract

The 5G mobile telecommunication network is becoming known as one of the finest communication networks for transmitting and controlling emergencies due to its high bandwidth and short latency. The high-quality videos taken by a drone, an incorporated Internet of Things (IoT) gadget for recording in a catastrophe situation, are very helpful in controlling the crisis. The 5G mm-Wave frequency spectrum is susceptible to intrusion and has beam realignment concerns, which can severely reduce Transmission Control Protocol (TCP) effectiveness and destroy connections. High-speed devices and disaster zones with multiple barriers make this problem significantly worse. This research offers a Deep-Learning-oriented Congestion Control Approach (DLCCA) for a catastrophic 5G mm-Wave system to solve this problem. By analyzing the node's transmitted data, DLCCA predicts when the network will be disconnected and reconnected, adjusting the TCP congestion window accordingly. To accomplish this, the proposed approach estimates the bottleneck link's queue length using the average Round Trip Time (RTT) and its data collected across the connection.

Consequently, the proposed approach can use this buffer size to examine the congestion state and differentiate it from the randomized loss situation. This would stop the window length from getting smaller, increasing the amount of data transferred and speeding up the recommended method. Additionally, DLCCA frees up bottleneck bandwidth. The research provides simulated tests for TCP DLCCA compared to Newreno, Cubic, Compound, and Westwood while sustaining a two-way connection under heavy load and a wide range of randomized loss rates using the networking simulation NS-2. Experimental results show that DLCCA performs better than other TCP variants and significantly boosts throughput.

Keywords – Deep learning, Congestion control, 5G, Transmission Control Protocol

1. Introduction to the congestion control algorithms under disaster 5G networks

Numerous recent natural catastrophes, such as the tsunami in Asia, the magnitude 9.0 earthquakes in Japan, and the storms in the United States, threatened human lives [1]. Natural disasters occur worldwide, taking lives and creating significant financial damages in addition to uncommon climatic phenomena. To reduce injuries, it is essential to identify a disaster as soon as possible and to communicate pertinent information accurately and quickly, such as critical circumstances and action directives, to everyone in the disaster zone [2].

The present equipment (such as Long-Term Evolution (LTE) ground stations and WiFi Access points) is damaged during a catastrophe, which limits the ability to transmit necessary data [3]. Unmanned Aerial Vehicles (UAVs) outfitted with the Internet of Things (IoT) devices for photography that rove and collect photographs of the catastrophe site using a small 5G base station are one solution to this problem [4, 5, 6]. UAVs capture high-definition video for crises and deliver it instantly to the transmission network via the 5G core architecture. This movie could be used to aid in rescue functions or broadcast to everyone in a crisis area. For successful usage in emergency administration and life-saving treatments, high-quality images must be sent without interruption (high connection) and with minimum latency. A viable use case for 5G networks is delivering urgent information since it can provide high-throughput (increased mobile connectivity) and rapid and precise answers (ultra-dependable and lower latency).

5G networks employ the millimeter wave (mmWave) range, which has a wide frequency range, to enable high bandwidth [7]. Although mmWave has a huge capacity, it has a significant path deterioration and high-quality factor, necessitating beamforming methods. Fortunately, the 3rd Generation Partnership Project (3GPP) 5G standardization groups have investigated and suggested beamforming techniques for 5G networks. Additionally, there are several problems with wireless connections that reduce the effectiveness of data transfer, such as video broadcasting, latency spreading, and random failures.

Unpredictable loss occurs if there are problems with wireless technology or periodic difficulties with hardwires [8]. The primary cause of communication failures is randomized losses, and errors can infect transmissions. Wireless media are more prone to transmission errors than wired media because of distortions and aging, significant bit error ratios, and concealed or exposed terminal difficulties. Disturbance, which alters the data supplied and causes the information to be conveyed to the destination incorrectly, is one of the fundamental problems with data transmission between receivers and transmitters [9]. A high bit error rate occurs in wireless and wired connections when there is an imbalance between the amount of transmitted and received data. It happens when there are problems with the medium linking the transmitters and receiver, such as optic lines, Asymmetric Digital Subscriber Lines (ADSL), or wireless telephones [10].

The research continues to investigate a better variability that may improve the effectiveness of data transmission in wireless links, even though the abovementioned variants discern between randomization losses and congestion loss to some extent. The DLCCA, congestion control approach, is designed for disaster environments and increases performance. TCP

DLCCA has made sender-side changes to the TCP Reno technique. Because standard TCP uses the segment's most significant sequenced number throughout the fast recovery procedure, it differs from other TCP variants. The end-to-end TCP technique, which delivers high efficiency over wireless connections, does not reduce the slow start criteria and congested intervals when a randomization loss is found. The standard TCP versions will perform worse in the presence of piggybacking streams and a large traffic requirement (A), where A is a defined congestion limit. In contrast to standard TCP, which merely employs a predefined bottleneck buffering limit, this research provides a TCP DLCCA. The study conducts extensive simulation testing to show the effectiveness, which is suitable for the two cases discussed above in deficient networks with randomized errors.

The results of the study are summarized as follows:

- The research looked at and concluded how TCP was affected by the terrible 5G mmWave platform and technical issues (beam misaligned and obstruction issues).
- The research created a Deep Learning (DL) algorithm for the 5G mmWave network, which anticipates obstruction length based on motion, and location. It acquired the TCP transmitters' Signal Noise Ratio (SNR) values. The proposed DL model is independent of the User Equipment (UE) mobility concept and has an accuracy rate of 90% or above for forecasting obstruction duration (TCP senders).
- The proposed TCP employs the necessary congestion control techniques after distinguishing between a brief link disruption and actual congestion.
- The research discovered that the proposed TCP performs superior to other existing TCPs in all configurations with the 5G mmWave environment, such as the disaster site (sports complex, smart city, inside, etc.).

The rest of the article is listed in the following manner. The background and history of the congestion control models in 5G and disaster areas are listed in section 2. Section 3 deals with the proposed Deep-Learning-oriented Congestion Control Approach (DLCCA) are designed, and the outcomes and experimental findings are enumerated in section 4. The conclusion and the overall results of the proposed congestion control algorithm are shown in section 5.

2. Background to the congestion control models in 5G and disaster areas

The standard TCP variants are one of the network's main transport layer methods. There have been many different TCP versions proposed as an outcome. In this section, the research provides a brief overview of prior studies on three various kinds of TCPs: conventional TCPs, 5G mmWave TCPs, and machine-learning TCPs.

2.1 Traditional TCP variants

CUBIC, a congestion control technique for TCP, is now Linux's standard TCP technique [11]. The approach transforms the current TCP protocols' linear window expanding algorithm into a cubic proportion, making TCP more extensible over quick and long-range networks. Additionally, it makes it possible for flows with various Round-Trip Times (RTT) to share capacity more fairly by maintaining the window expansion independent of RTT. As an outcome, the congested window grows for each of those flows at the same pace. When the window is stabilized, CUBIC increases the window size violently and gently depending on how far away from the maximum it is.

TCP Westwood, a transmitter-side improvement to the TCP congested window technique, beats TCP Reno on communication networks [12]. The increase is particularly noticeable with lossy channels since TCP Westwood employs end-to-end capacity forecasting to differentiate between the sources of traffic problems (congested highways or wireless link errors), which is a significant issue in TCP Reno. The main aim is to assess the regularity of the association by monitoring the rate of transmitting data at the TCP source. The approximation is utilized to determine the congestion duration and threshold following a congestion occurrence, following three repeated acks, or a timeout. The recommended method is particularly effective over wireless connections since current TCP systems typically misinterpret periodic failures caused by accessible radio difficulties for congestion, resulting in an exaggerated window reduction. Experimental research has revealed improvements in fairness and operational efficiency.

The research has discussed several ways to improve TCP, including a novel timeout technique, a state-of-the-art congestion control technique that reduces the amount of extra network throttling a connection needs, and an altered slow-start technique [13]. The simulation results show that Vegas' implementation of TCP beats the Reno version of Unix by 37-71%, with one-fifth to one-half as few packets being resent. Furthermore, the research has demonstrated that Vegas is just as fair as Reno, is reliable, and has no detrimental consequences on latency.

2.2 TCP in 5G mmWave network

This study presents a unique TCP relying on a fuzzy controller to avoid performance deterioration in 5G networks [14]. Fuzzy sets are used in the novel system's congestion control phase to dynamically change the sending rate and lessen the consequences of obstructions. The theory's ultimate objective is to manage the transmitting rate depending on the system's condition to maximize performance. Furthermore, it tries for minimal latency and reduces the mean sending rate to avoid buffer exhaustion.

Wireless networks cannot employ the current Multipoint TCP (MP-TCP) bottleneck control approach because it was designed for 5G networks. By distinguishing between loss due to congestion and radio channel failures, the RTT allows for various Veno congestion-controlling approaches; a unique MP-TCP congestion-controlling technique is developed in this work to enhance support for wireless communication systems [15]. The proposed system employs a novel backlog estimation method that distinguishes between errors due to congestion and random wireless failures while accounting for the total buffering length. The Veno approach will use these estimations to balance the ideal RTT of each sub-flow and decrease the rearrangement delay.

The most popular transport layer technology, TCP, affects by considerable performance decrement due to the fast-varying wireless environment of the 5G transmission. This study presents a congestion-controlling method that assures adequate performance in 5G systems without significantly impairing TCP fairness [16]. The recommended approach, a version of the high connectivity structure, Scalable TCP (S-TCP), delivers a more dependable efficiency than the available congestion control technique in 5G environments with only minor tweaks.

2.3. TCP with learning algorithms

As shown in this study [17], an intermediate router (like a phone provider) may detect the sending status of the TCP client linked to a TCP flow by only watching the TCP data. The research demonstrates how the intermediary router may predict the TCP client's Congestion Windows (cwnd_) size. The technique may be used to forecast the state of other receiver TCP connections. The approach for identifying the cwnd_ within a flow utilizing passive data acquired at intermediate nodes is a broad, deep learning-based potential advancement.

The research recommends the Machine Learning Losses Differentiation Approach (ML-LDA) for managing cellular TCP overload [18]. To distinguish between transmission failures brought on by congested and wireless link characteristics, ML-LDA employs Multi-Layer Perceptrons (MLP). In the occurrence of random errors, the congestion control doesn't tighten the additional traffic; instead, it classifies the source of losses depending on the learning results. The research incorporated the technique into the Linux kernels and created a test environment where package drops occur irregularly to verify the viability of the proposed network problems.

The study suggests a congestion control method that ensures enough capacity in 5G mmWave systems and doesn't materially compromise TCP equality [19]. Through minor adjustments, the suggested method, a variation of Scalable TCP (S-TCP), a high-speed network architecture, offers a more reliable efficiency than the current TCP congestion management method in 5G systems. The suggested mmWave Scaling TCP (mmS-TCP) method achieved throughput up to 2.3 times greater than CUBIC in the simulated analysis.

Machine Learning (ML) has successfully resolved complex and large-scale problems, and academics have begun to place less emphasis on rule-based approaches and more on ML-based methods [20]. This paper presents an overview of current learning algorithms for end-to-end congestion management. This work briefly introduces the relationship between learning algorithms and traffic management. The research reviews recent studies that employ machine learning to reduce congestion problems. These initiatives either help the operators work more effectively or help them choose the best action to minimize bottlenecks.

Additionally, these studies use packet-based data to foresee or enhance network traffic control (congestion windowing size, round trip time, periods of acknowledgments, etc.). As a result, congestion control techniques will only be able to address obstruction concerns brought on by mobility problems. This problem will undoubtedly worsen, given the continuous mobility and multiple obstructions in the 5G mmWave catastrophe infrastructure. The study offers a deep learning framework relying on the movements, location, and gathered Signal Noise Ratio (SNR) information.

3. Proposed Deep-Learning-oriented Congestion Control Approach

The research discusses the 5G mmWave network concept and associated problems for the catastrophe area in this segment. The study presumes an uplink situation in which firefighters with digital news collecting cameras and Unmanned Aerial Vehicles (UAV) for comprehensive coverage of disaster locations send the footage to a broadcasting network or control units. They utilize the 5G connection to transmit high-definition videos to broadcasters and emergency operation centers in basic data form without compression. Nevertheless, a data speed of the order of Gigabits per second (Gbps) is necessary to send uncompressed pictures without latency, enabling a 5G mmWave system with a broad capacity.

The beamforming technique is crucial for mitigating high route loss in 5G mmWave systems. The produced beams provide high antenna gain among the 5G ground system and the transmitter endpoint (transferring UE); nevertheless, it is susceptible to obstructions because of the beam's positional accuracy. Additionally, the reception gain is decreased, which lowers the SNR level, when the orientations of the generated beams connecting the sending and receiving stations are not aligned. The transmission UEs have unpredictable movement in the current 5G mmWave networking topology, which might cause connectivity issues.

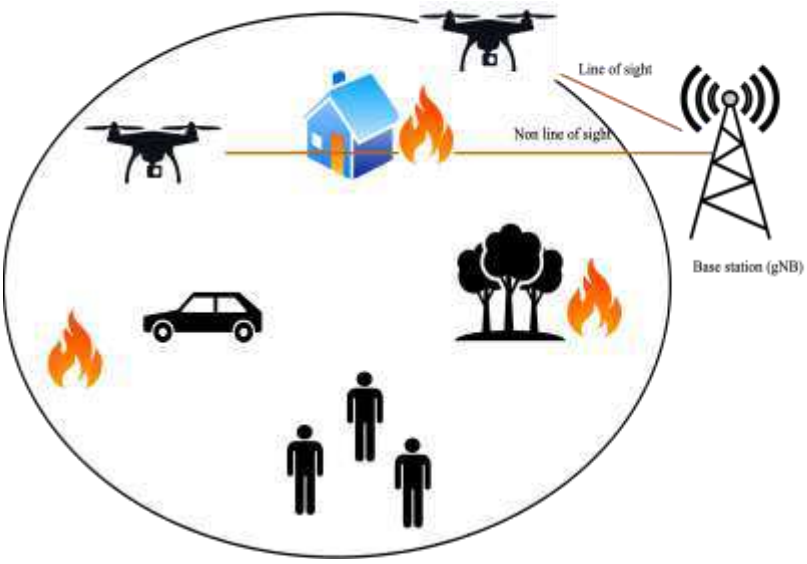

Fig. 1. 5G mmWave networking topology for a disaster area model

The 5G mmWave networking topology for a disaster area model is shown in Fig. 1. In Line-Of-Sight (LOS) settings, UAVs send videos of disaster events to a 5G ground station. Signal transmission in the mmWave range is impossible; nevertheless, Non-Line-Of-Sight (NLOS) is created because of obstructions like trees or structures [21]. Fast-moving UAVs and camera operators covering catastrophe scenes are more prone to encounter these issues. The UAV and ground Node Base (gNB) wavelengths are appropriately matched, and the transmitter SNR is vital. Still, the cameraman's and the gNB's wavelengths need to be in alignment, making it impossible to capture the signal.

3.1 Deep learning architecture

The proposed congestion control algorithm for mmWave systems has blocked and beam misalignment issues, which are discussed in this section.

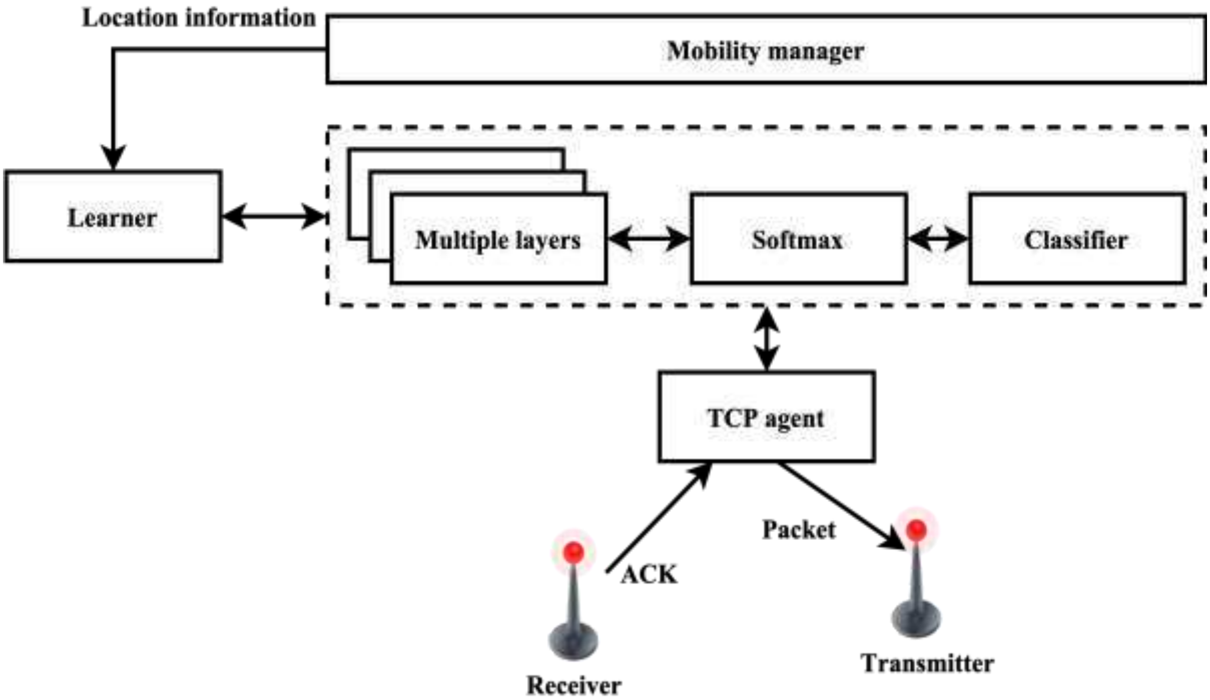

Fig. 2. A deep learning-based Transmission Control Protocol

A deep learning-based Transmission Control Protocol is designed and depicted in Fig. 2. A deep learning model analyzes the user's mobility based on location information. The deep learning model has multiple processing layers, softmax, and classifier layers [22]. This approach is attached to the TCP agent, which is further used for transmitting a data packet and receiving an acknowledgment packet. The TCP sender includes a predicting unit, a mobility controller for handling speed and position data, a learner engine for training, and a TCP actor for figuring out TCP behaviors. Each element fulfills the following functions:

Using data from the movement management and transmitters, a learning agent determines the size of a network problem, and a prediction determines whether a TCP Retransmission Time out (RTO) is a short-term or long-term disconnection based on the acquired data [23]. TCP agent manages the Current Window (cwnd_) value depending on the data anticipated by the prediction. At the same time, movement management is a component that offers the current position details and speed vectors of the TCP transmitter.

Obstruction and beam misaligned result in intermittent connections being unplugged and initializing cwnd_ when a portable Transmitter transmits in the mmWave frequency. If there is an obstruction issue, the TCP user's movement will determine how long it takes to get past the obstruction and how long it takes to detach if the converse is true. The TCP operator can perform the following steps when a timeout occurs due to wireless channels. To keep the data throughput from falling after a brief network loss, the length of the cwnd_ is preserved. In the reverse situation, the cwnd_ is initiated and starts the congestion control stage.

The TCP maintains the size of cwnd_ in beam realignment; however, because the beam scouring approach is used after 100–250 ms, the networking loss cannot last longer than 100–250 ms. As a result, the system state is recovered in 100–250 ms, even in transmission errors. To put it another way, controlling the size of cwnd_. Nevertheless, when it notices a transmission loss occurrence, the standard congestion control activates the length of cwnd_.

Considering the analyses above, the research arrives at the following conclusion:

- If the connection problems last longer, the cause is network traffic or signal-obstructing objects. Therefore, initializing the cwnd_ length is preferable.
- A brief connectivity issue is a transitory signal disruption that may be quickly resolved. Therefore, it is preferable to keep the length of the cwnd_.
- If the line of sight between the transmitter and the gNB is created and the connection still exists, the length of the cwnd_ is increased.
- When a network congestion event happens, the suggested DLCCA predicts the length of the network problems to decide whether to retain the cwnd_ size.

3.2 Congestion control approach

The traffic management method's primary mechanism operates via the transport layer. These functionalities are modified according to the network's size [24]. The area allows for a detailed examination of the number of endpoints needed to complete specific tasks.

A broadcaster and a receiver must be connected in the data transfer mechanism. A specific endpoint and the host establish a relationship. To monitor cwnd_ and Slow Start Threshold (ssthresh_), it sends the original message and awaits acknowledgment (ACK_). Cwnd_ and ssthresh_ are recognized when the receiver returns ACK_, and thus overcrowding is controlled. The misplaced stage is recovered if the receiver does not perform ACK_. The slow-start phase is created if cwnd_ is lower than ssthresh_. The congested mitigation stages are run whenever cwnd_ crosses ssthresh_. Until every communication is received, this procedure is repeated.

3.2.1. Mathematical model

The results of a traditional or original TCP simulation in a 5G scenario revealed that cwnd_ rose gradually and linearly. When cwnd_ exceeded ssthresh_, it was believed that cwnd_ would after that increase as each ACK_ value increased in line with a predetermined interval. Details of the generated model are discussed on how the theoretical architecture is visualized.

- Enhanced slow start

The improved Slow-Start (SS) stage is started after a lengthy delay or when data transfer begins in an anonymous 5G environment. At this point, the DLCCA begins scanning the network to determine the available capacity. Ssthresh_ is thought of as the indication to display the accessible ability to prevent methods that use more resources than are available. A retransmission timer can identify the slow-start period, which follows the recovery after transmission errors. The cwnd_ will be raised after each acknowledgment if it is less than or equivalent to ssthresh_.

Consequently, an exponential increment will be made to the cwnd_ value. The transmitter must adhere to the algorithm's permissible requirements during this stage. Equation (1) demonstrates the slow start mechanism in which the sending rate is increased by one for every acknowledgment received.

$$wnd_x = wnd_{x-1} + k \quad (1)$$

The current sending rate is denoted wnd_x, the previous sending rate is denoted wnd_{x-1}, and k is either the preceding recognized remaining information chunk(s) or the Maximum Transmitting Units (MTU) of the target. The total amount of the prior pending recognized data portions is ACK_. The typical slow-start equation is given in Equation (2).

$$\Delta wnd_x = min\{D_{ACK}, MTU\} \quad (2)$$

The maximum sending rate is set based on the total value of acknowledged data and the MTU value. The suggested slow-start equation is expressed in Equation (3).

$$\Delta wnd_x = min\{D_{ACK}, MTU\} + wnd_x/N \quad (3)$$

The data acknowledged is denoted D_{ACK}, and the number of acknowledgments received in the current RTT is indicated N. Based on many performance criteria, the variable N is an integer ranging from 1 to 100. These elements include network performance, congested windows, number of lost packets, number of transmitted packets per time units, and number of packaging retrieved per time. The selection process aims to identify the component that significantly impacts the congestion-controlling mechanism. The best N is determined based on the RTT value. The results of the efficiency criteria decide what value is optimal. The requirements to establish the optimum result are the highest congestion window, optimal queue length usage, highest number of accepted and transmitted packets, highest performance, and most minor transmission loss. The severity of packet loss increases when N is greater than 8. This incident has an impact on the queue length. In an improved slow start, the value of N varies from 1 to 100 depending on these factors, the operational component findings, and the testing findings.

- Enhanced congestion avoidance

When both the cwnd_ level or the volume of transferred data surpasses the threshold, Congestion Avoidance (CA) augmentation is established. Therefore, when cwnd_>ssthresh_, the congestion minimization will improve cwnd_ by 1(MTU) per RTT [25-27]. The transmitter either possesses the cwnd_ quantity or the sent data that exceeds the balance owed to the transmission location. Because cwnd_ is constantly checked with ssthresh_, the congestion reduction method operates in tandem with slow-start. The slow-start phase will be generated if the cwnd_ is below or equivalent to ssthresh_; alternatively, the congestion control stage will predominate. But when different cwnd_ pathways allow different phases to occupy them, there is communication between these stages. When cwnd_>ssthresh, the MTU is calculated by the maximum transfer unit per round trip time. The typical congestion control formula is expressed in Equation (4).

$$\Delta wnd_x = MTU\ per\ RTT \tag{4}$$

The incremental count for the next RTT is incremented by only one MTU per RTT. The suggested congestion control equation is written in Equation (5).

$$\Delta wnd_x = MTU\ per\ RTT + wnd_x/N \tag{5}$$

In contrast to the standard congestion management formula, congestion control reduced to this level can speed up the congested control procedure. Additionally, the congested control is optimized by reducing congestion minimization and increasing slow start. Therefore, as stated earlier, the suggested congestion control formula must be changed into a non-homogeneous procedure.

- Distinguish random loss from congestion loss

The queuing length limit N is measured by DLCCA using the constant number A, equal to 0.55. When the system employs this number, it outperforms some methods in terms of throughput, whereas when A values are more significant than 0.55, throughputs are equal. According to the standard TCP protocols, independent of the traffic situation for each customer separately, the cwnd_ for all senders is changed when several links transmit data. As a result, congestion periods for all customers may increase needlessly, lowering the number of delivered packets and worsening performance. This is seen with the two significant transmitting load that causes obscene network congestion. This prompted the network to examine standard TCP variants and think about independently changing the N-threshold for the queue for each customer.

The sender measures the minimal and averaged RTT, which DLCCA uses. Therefore, the system considers a variable queuing size limit of N based on the receiver's maximum advertised window and renders it more accommodating for each responder. This implies that the transmitter will calculate the median RTT and that its lowest is observed, resulting in various client information transfers. Using the revised limit, DLCCA determines the threshold (T) in Equation (6).

$$T = \frac{RTT_{avg}}{RTT_{min}} \qquad (6)$$

RTT_{avg} is the aggregate of RTT measurements for all times, and RTT_{min} is the shortest RTT any sender has ever experienced. The congestion control algorithm is shown in Algorithm I below.

#Algorithm I
If an ACK_ is received at the sender
$RTT_{min} = min\{RTT_{new}, RTT_{old}\}$
$RTT_{avg} = \frac{\sum_{i=1}^{N} RTT_i}{N}$
Compute $L_x = (RTT_{avg} - RTT_{min}) * M$
Compute $L_{max} = \max\{L_x, L_{old}\}$
Compute $N = T * L_{max}$
If $(L_x > N \&\& Ack_{max} > Seq_{max})$
If $wnd_x > rwnd_x/2$
$ssthresh\_ = \min(wnd_x, rwnd_x)/2$
Else $wnd_x = wnd_x + 1\ per\ RTT$
If $ssthresh\_ < 2 * MTU$

$ssthresh\_ = 2 * MTU$
End if
$wnd_x = ssthresh\_ + 3 * MTU$
$Seq_{max} = \max\{sent\ (Seq_x)\}$
Else
$wnd_{old} = wnd_x$
$wnd_x = wnd_x + 3 * MTU$
End else
End if

The present transmission rate is denoted wnd_x, and the previous sending rate is denoted wnd_{old}. The previous RTT is denoted RTT_{old}, the minimum RTT is denoted RTT_{min}, the average RTT is expressed RTT_{avg}, and the next RTT value is denoted RTT_{new}. The maximum advertised receiver window is denoted $rwnd_x$, the current sequence number is denoted Seq_x, and the maximum sequence number is denoted Seq_{max}.

The findings demonstrate how DLCCA boosts performance when customers transfer various quantities of information depending on RTT measures.

3.2.2 Development phase

The enhanced TCP congestion-controlling technique in the 5G ecosystem is discussed in this study. Enhanced slow-start and congestion control methods must be used to accomplish the third goal. The limitations of traditional congestion management in the 5G context were resolved using the upgraded methodologies. The final form of DLCCA was developed using various developmental techniques based on an enhanced congestion control system that takes advantage of DL features. Implementing a two-stage assessment with different contexts was done to create DLCCA. The congestion controls offered the modified window administration in the initial phase. DL method assessment parameters were used: queue length, performance, packet drop, and cwnd_. The new methods use slow-start cwnd_ and congestion minimization to perform effective window administration.

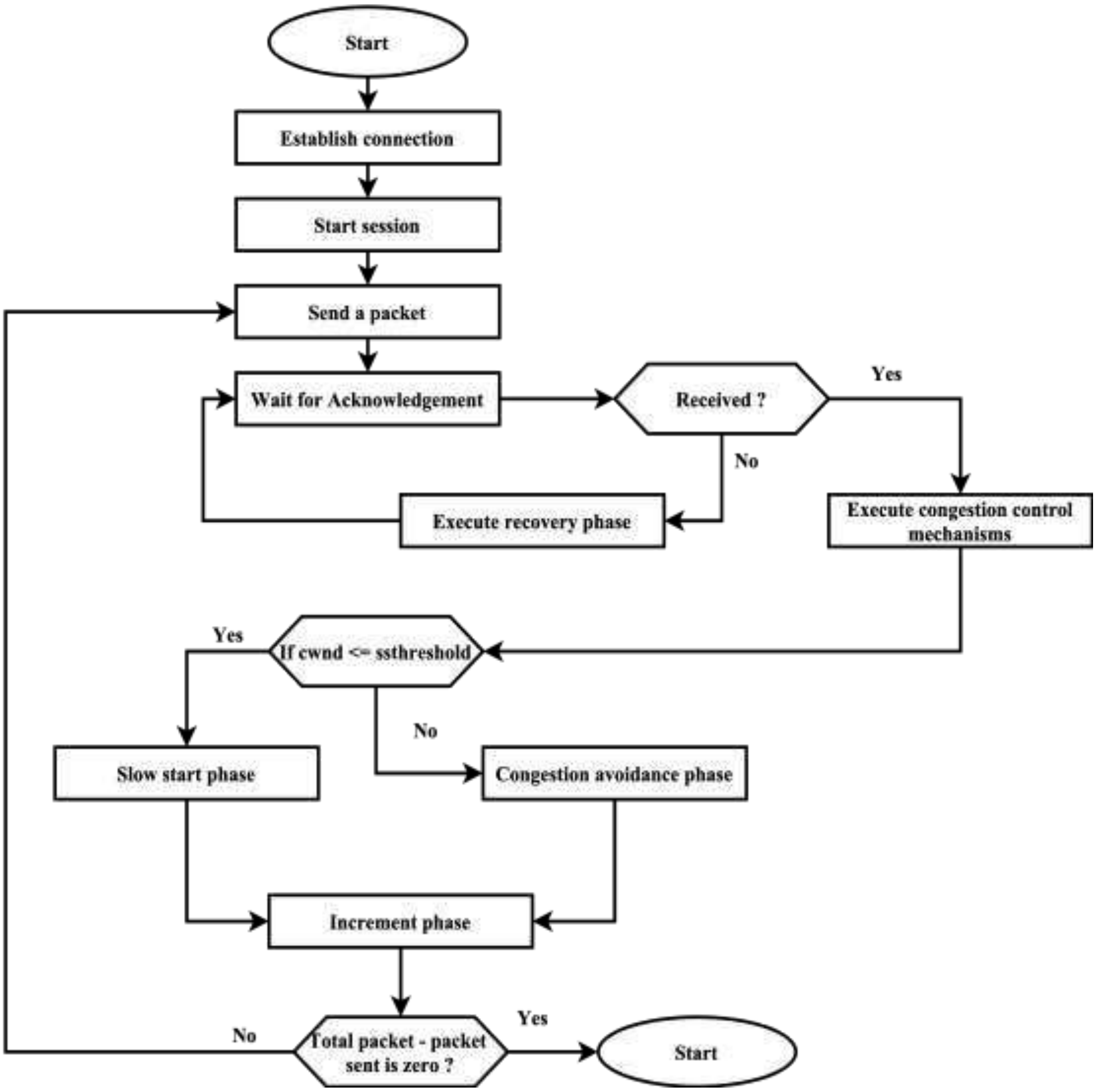

Fig. 3. The workflow for the development phase of the DLCCA

The workflow for the development phase of the DLCCA is designed, and the result is shown in Fig. 3. Initially, the connection is established between the sender and the receiver, followed by the session starting. A packet is sent from the server, and the sender waits for the acknowledgment. A slow start or congestion avoidance process is called if the ACK_ is received based on the congestion control model and ssthresh_ value. The recovery phase is called if ACK_ is not received within the RTO. The session and connection are closed when all the packets are transmitted from the sender.

All potential experiments, including associated situations, have been explored and provided at this stage. Two investigations were planned and constructed based on these steps. The following section goes into the specifics of these tests. The enhanced congestion management techniques use modified strategies linked to slow-start and congestion mitigation systems.

3.3 Applying the deep learning approach

J48 is produced during this stage of model development. Numerous sectors employ deep learning techniques (such as grouping) for tasks, including categorizing student academic achievement and improving the achievement of network components. The DL method has more responsibilities than other data mining techniques. According to earlier research that used the method in various disciplines, including healthcare, e-government, wireless sensor networks, mobile multifactor authentication, and penetration testing, the DL technique has encouraging results as a component of computer vision.

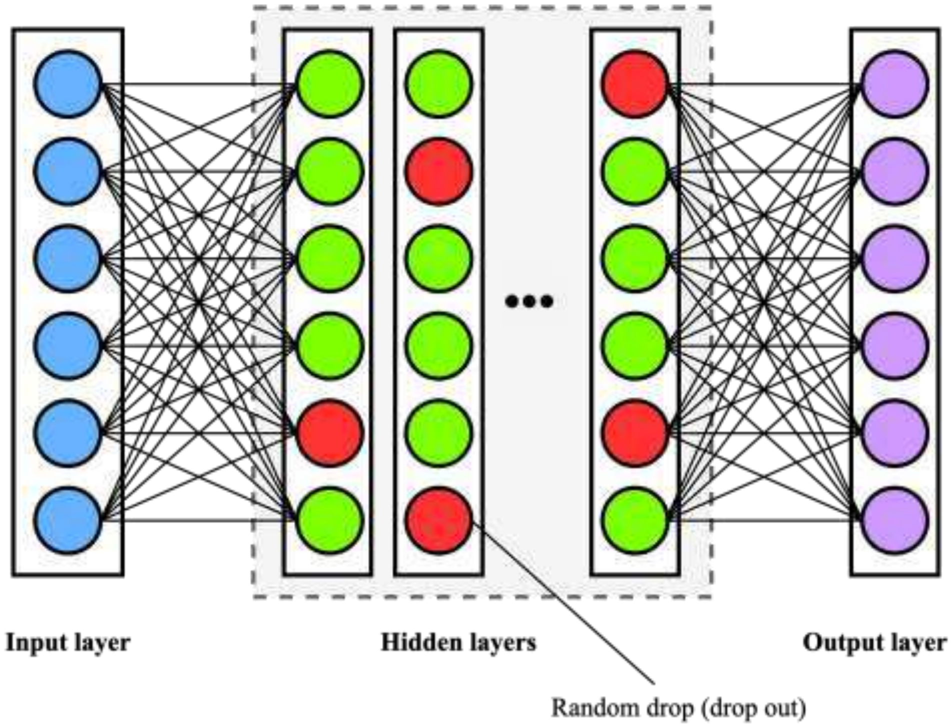

Fig. 4. The deep learning architecture

The deep learning architecture for the congestion control algorithm is shown in Fig. 4. The architecture consists of input, output, and multiple hidden layers. The DL method creates an orientated tree network based on learning information for categorization and prediction. The root component of a tree graph grows into a subtree and terminates with a leaf node. The features that reflect the dataset's properties are encountered on the route from the roots to the leaf component. This route might be considered for the forecast of upcoming instances. The resultant tree is constructed and translated using IF condition expressions. The system can use the reliable and practical deep learning technique to uncover hidden connections in small and extensive databases. A tree is built in three phases: building, data gain calculation, and trimming. The following fundamental actions are part of the building phase:

- Check to see whether all concerns fall under the same category. As a result, a leaf with a classifier is a tree.
- Determine the data gain and the data for one attribute's component.
- Find the best dividing characteristic based on the current selecting criteria.

The splitting will result in a tiny, effective tree if it is predicated on high profit. A pruning strategy is used in the concluding stage to deal with classifiers and misfits. Measurements with weakly specified instances can be classified through pruning. Trimming is divided into two categories. Trimming is done when a tree is created, and post-pruning is done after the tree is built. The separate-and-conquer rule structure provides the foundation for pruning execution. The simulation outcomes of the proposed DLCCA are analyzed and discussed in the next section.

4. Simulation outcomes and findings

The research assesses the suggested DL-performance TCPs in this section using the mmWave NS-2 simulator. The forecasting efficiency of the suggested DLCCA is first evaluated. The simulation area is 1000m x 1000m. In the architecture, the gNB and the UAV are connected; every 100–250 ms, the gNB automatically sweeps the beam. Furthermore, it presumptively considered that UAV's velocity is uniformly distributed between 54 and 90 km/h. The research gathered Signal to Noise Ratio (SNR) information for around a day to get training information.

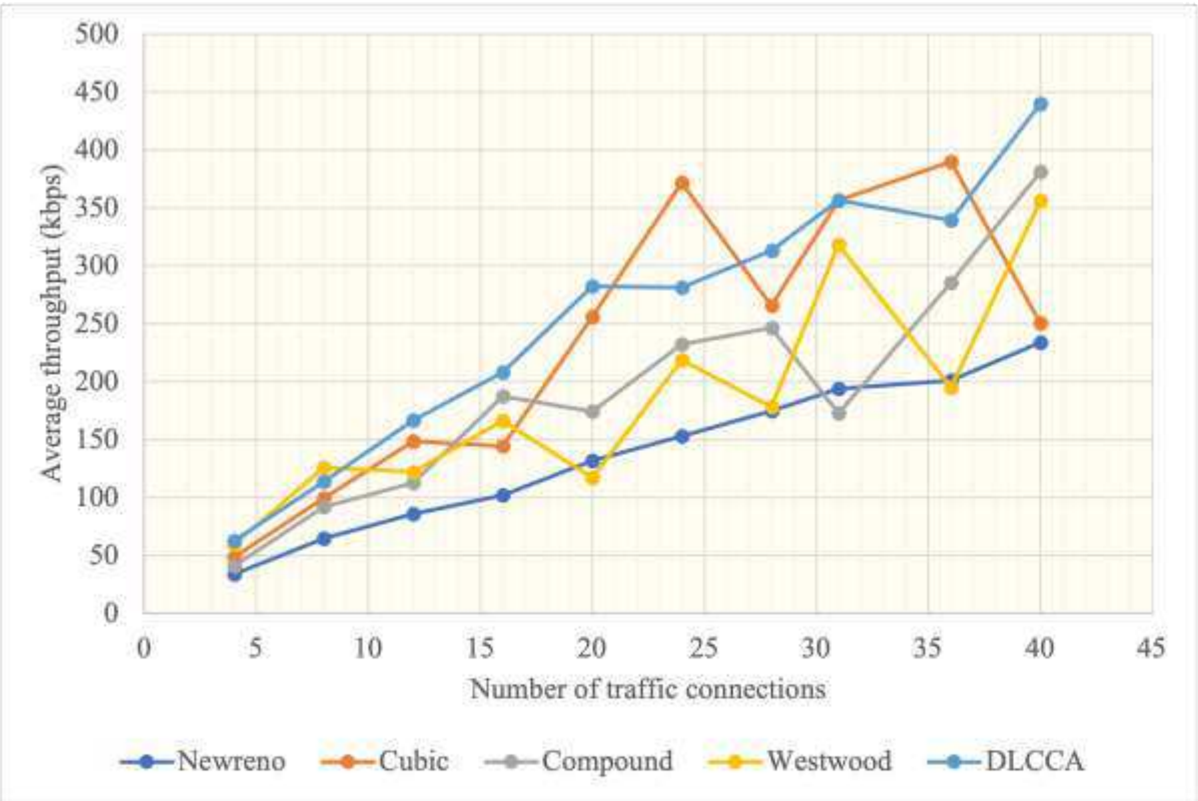

Fig. 5. Average throughput comparison over traffic connections

The average throughput comparison of the DLCCA with the existing New Reno, Cubic, Compound, and Westwood over traffic connections are shown in Fig. 5. The number of traffic connections is varied from 4 to a maximum of 40 with a step count of 4 traffic connections. As the traffic connections increases, the respective throughput of the congestion control algorithm increases. The proposed DLCCA outperforms the existing models with the assistance of a deep learning algorithm. The throughput is increased at the highest traffic conditions because there may be the possibility of sending more number packets at a time.

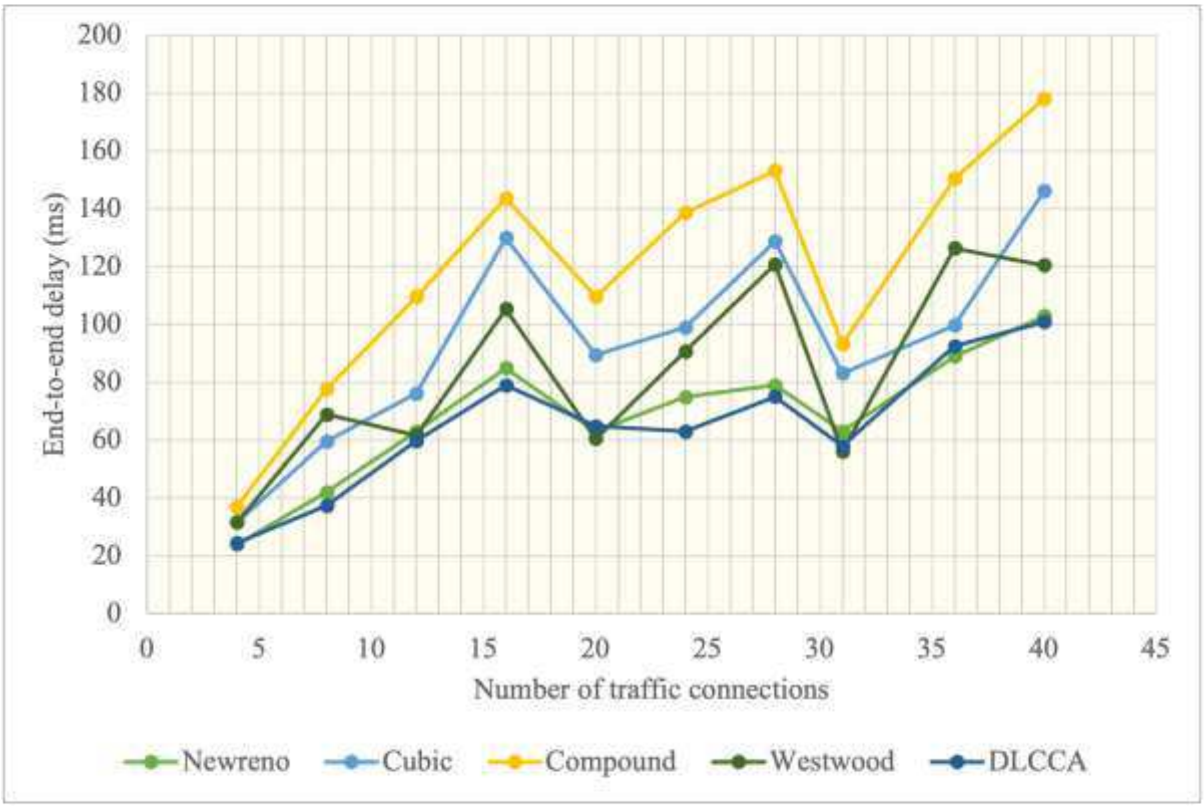

Fig.6. End-to-end delay comparison over traffic connections

The end-to-end delay comparison over different traffic connections is analyzed, and the result is shown in Fig. 6. As the number of traffic connections increases, the respective end-to-end delay increases because there may be a possibility of buffer build-up in the intermediate nodes. The compound exhibits higher delay because the congestion control model focuses only on higher throughput but fails to reduce the end-to-end delay. The DLCCA with deep learning reduces the end-to-end delay and enhances the throughput. The end-to-end latency at the lower traffic conditions is more minor because the possibility of queue build-up in the intermediate nodes is slight. Thus, the overall delay reduces.

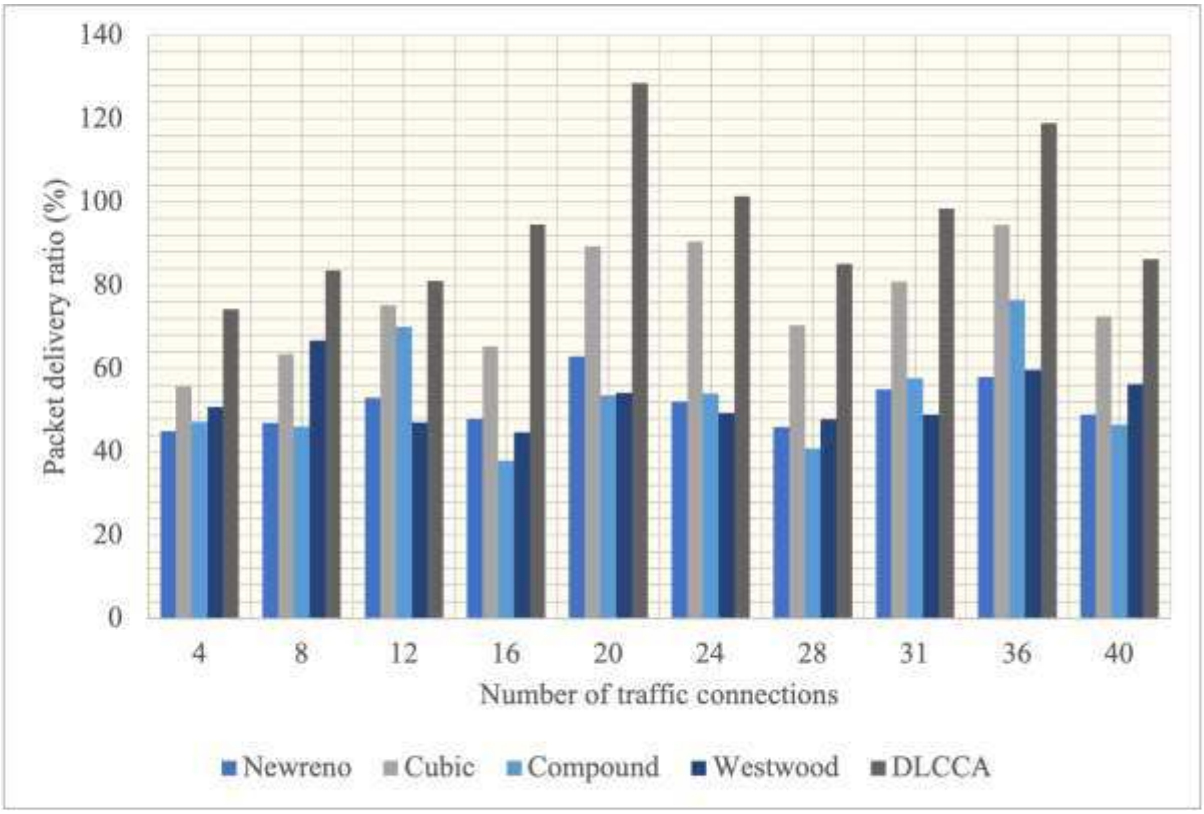

Fig.7. Packet delivery ratio comparison over traffic connections

The packet delivery ratio comparison of the different traffic connections is measured, and the experimental findings are shown in Fig. 7. The proposed DLCCA results are compared with the existing TCP models, such as New Reno, Cubic, Compound, and Westwood. The experiment is done under lesser traffic conditions to higher traffic conditions. As the traffic condition increases, the respective packet delivery ratio also increases. The packet delivery ratio is indirectly related to the total packet drops in the environment. As the traffic conditions increases, there may be a possibility of buffer buildup and the chance of packet drop. The proposed deep learning model enhances the overall outcomes by analyzing and predicting the traffic network.

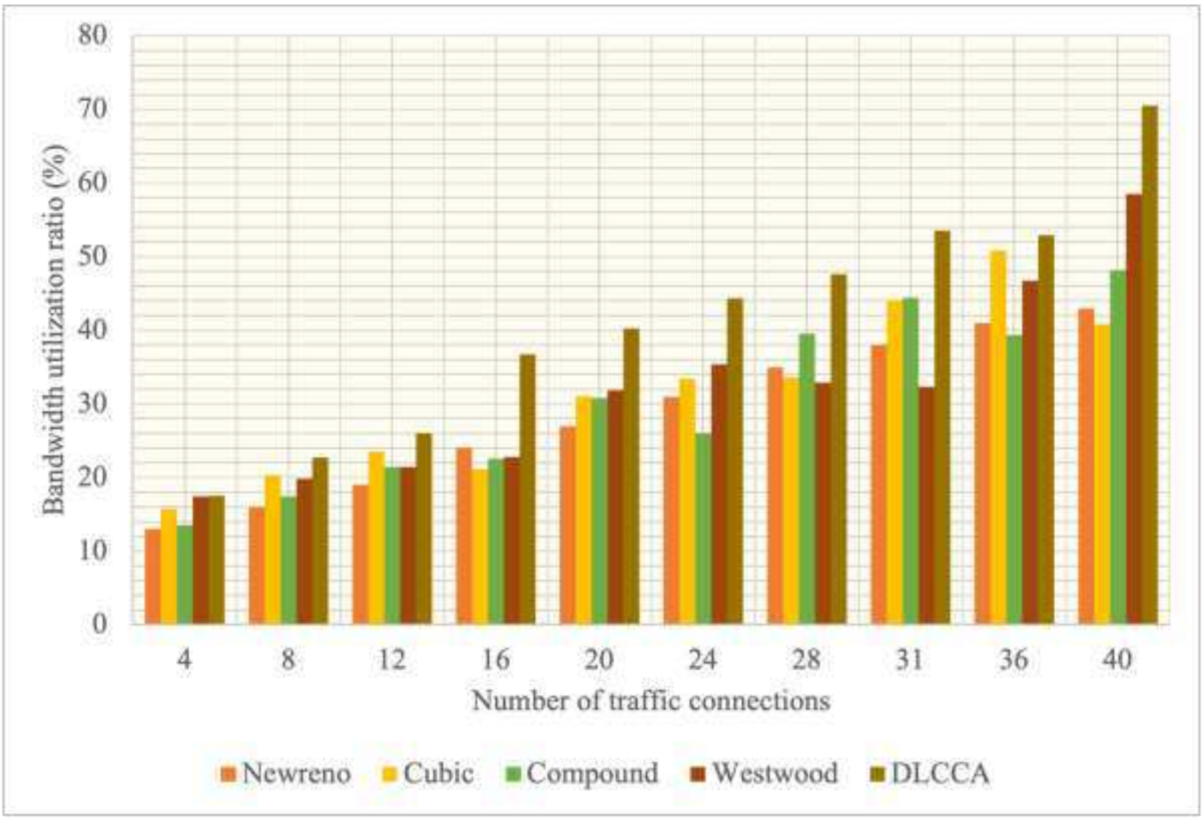

Fig.8. Bandwidth utilization ratio comparison over traffic connections

The bandwidth utilization ratio analysis of the proposed DLCCA model is done, and the results are compared with the existing congestion control algorithms in Fig. 8. The bandwidth utilization is directly related to the number of traffic connections. When the traffic connections exceed a maximum threshold, the bandwidth utilization reduces because there may be a possible buffer build-up and more packet drops. This leads to a more frequent sending rate reduction and thus reduces bandwidth utilization. The proposed deep learning model analyses and predicts the network conditions and helps to attain higher bandwidth utilization which helps increase throughput.

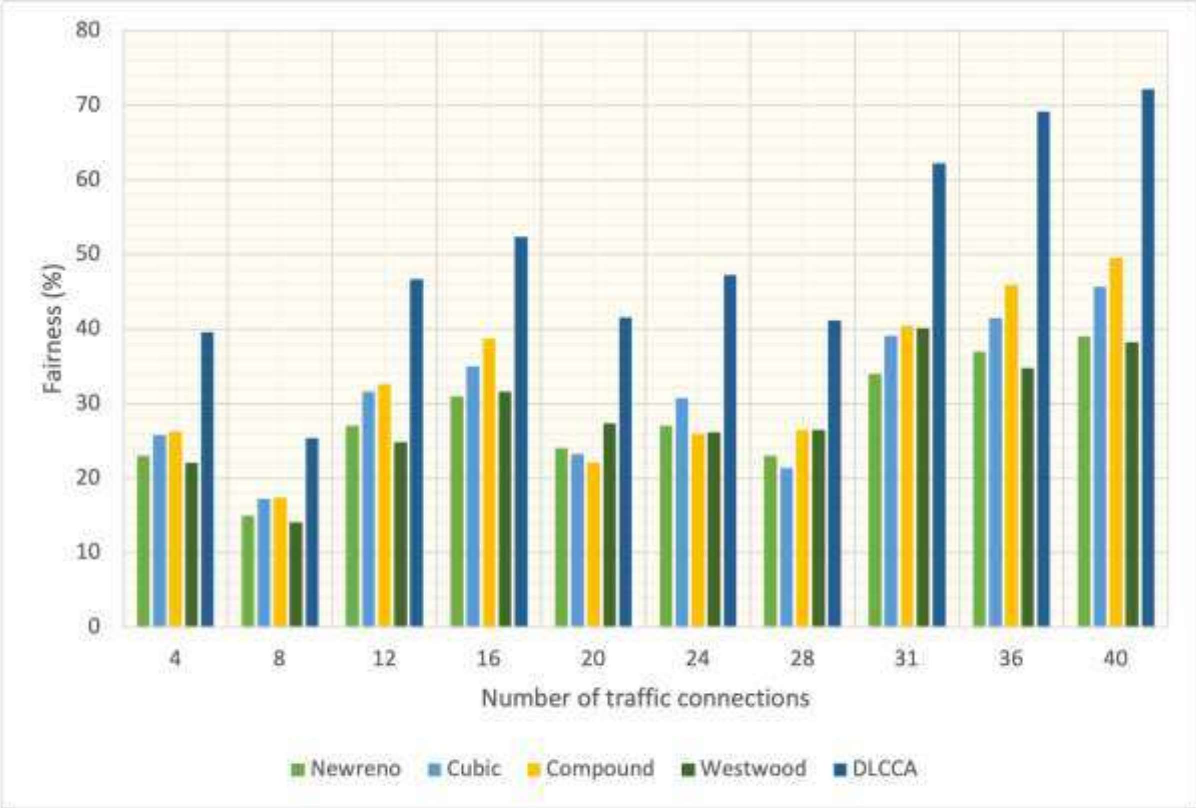

Fig.9. Fairness comparison over traffic connections

The fairness is computed in how the congestion control algorithm deals with traffic connections. The fairness comparison of the proposed DLCCA model with the existing models is analyzed and plotted in Fig. 9. The respective fairness also increases in the proposed DLCCA model with the assistance of the deep learning algorithm with respect to the growth in traffic connection. The existing models need to give importance to lower and higher bandwidth traffic. They blankly reduce the congestion window, and thus, the lower bandwidth users are affected. But the proposed DLCCA model understands the maximum capacity of the user and accordingly reduces when congestion occurs.

The proposed DLCCA model is designed, and the outcomes are computed in this section. The performance comparison exhibits the impact of the proposed deep learning-based DLCCA model in increasing network performance and reducing end-to-end delay and packet loss. The deep learning algorithm helps analyze and predict the network conditions and act accordingly, which is helpful in disaster conditions.

5. Conclusion and the findings

One of the best models for quick catastrophe reactions is the 5G mmWave system. The loss in signal intensity caused by the impediments and beam misaligned can be a component in dampening TCP effectiveness because of the features of the mmWave spectrum. This study proposes a Deep-Learning-oriented Congestion Control Approach for the 5G mmWave frequency spectrum in disaster conditions. Depending on node movement data and signal strength, the deep learning algorithm of the research calculates the channel disconnecting duration and forecasts the link disconnecting duration when there is a loss in the network. By executing correct sending window size management according to the projected time, which was proven using NS-2-based simulations, DLCCA was created to run without wasting mmWave capacity. The purpose of DLCCA is to enhance wireless networking efficiency when there are numerous connections and unexpected link failures. The two primary objectives of DLCCA are to reduce bottleneck congestion and distinguish between accidental loss and congestion losses. These two main objectives were achieved, and varied network systems topologies showed excellent throughput efficiency. The suggested model is not an innovative way to prevent connection errors because it is a loss-based TCP algorithm in which a packet failure occurs. Therefore, the deep-learning system in this research uses beam-reflecting technologies to eliminate intrusions in the 5G frequency band and beam management systems to offer a smooth connection atmosphere. The research will use the deep learning algorithm to study further reducing errors in the 5Grange.

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