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A3C Based Dynamic BitRate for Video Streaming in 5G Edge Assisted D2D Communication Using H.266 With Conv-DBN

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Abstract — *In 5G wireless networks, video streaming is challenging due to high video content consumption with higher resolutions. Video compressing technology is used to solve this problem. Due to the increasing of video-based applications, and the network faces high traffic issues that reduce video quality. To avoid this problem, D2D communication is introduced in a wireless network that communicates directly to the devices without any intermediate nodes, thus reducing traffic and enhancing video quality and performance of network cellular. To address these issues, we proposed the A3C-DBVS (A3C-Dynamic Bitrate for Video Streaming) method, which has five consecutive phases: high-quality video encoding, adaptive bitrate changing, and multipath selection, task offloading, and D2D based virtual clustering. Firstly, we perform video encoding to compress the video using the Conv-DBN-based H.266 video encoding technique, which compressed the video without reducing the quality. Secondly, the bitrate is adapted during video streaming to improve the video quality using the A3C algorithm by considering video priority level and SLA constraints. Thirdly, we proposed a multipath selection method to select the best path between source and destination using the best fitness-based equilibrium optimizer algorithm, thus reducing high packet loss during video streaming. Fourth, we proposed task offloading. If any latency is occurring during video streaming, the edge performs task offloading to avoid congestion problems. For that, this process used a delay-based task distribution algorithm. And finally, we proposed D2D based virtual clustering, thus increasing video quality and reducing congestion or traffic in the network. For D2D pairing, we create virtual clusters using Advance Fuzzy C Means (Advanced FCM) algorithm. The simulation is conducted in the NS3.26 network simulator, which evaluates the performance based on performance metrics such as throughput, latency, cluster purity, energy consumption, path fitness, PSNR, MOS, packet loss rate, and Goodput and jitter, and bandwidth utilization.*

Keywords — *Virtual cluster-based D2D, Adaptive bitrate changing, and video streaming. 5G, Edge, Video encoding (H.266), task offloading.*

I. INTRODUCTION

5G is the 5th generation mobile network. It is a new global wireless standard after 1G, 2G, 3G, and 4G networks [1]. 5G enables a new network designed to connect virtually everyone and everything, including machines, objects, and devices. 5G supports the multimedia services such as real-time video transmission, video conferencing. Among these services, video streaming has greater importance [2]. Because all of the users wants to perform video streaming over the wireless network. QoE is measured by low latency, energy consumption, bandwidth consumption, and high bitrate [3].In video streaming, the first process is video encoding. For encoding, high-definition video coding standards are used. ManyHEVCstandards are there, but H. 265 is more advanced than other standards in several ways [4]. The main difference between H.265 to different standards, H.265 reduces the file size and required bandwidth of live video streams [5]. The author in [6] used H.265 standard for video coding. H.266 is the latest video coding standard. It is used to improve the quality of the video by monitoring luma and chroma values [7]. These videos are transmitted via multipath over the 5G network. The author [8] uses the multipath selection for sending the video without any delay with congestion avoidance. 5G supports the Mobile Edge Computing (MEC) technology used for storing and serving a purpose. Using a single edge is always a drawback because many sources access the same edge simultaneously, which causes high latency and congestion [9]. To avoid this problem, use multiple edges, which distribute the tasks to available edges. This process is called task offloading. The load balancing was carried out by using various edges and offloading of tasks [10].

Device-to-device communication (D2D) is a crucial technology to enhance 5G performance [11]. D2D is direct communication between two devices without the involvement of any central point. It is used to improve the quality and also reduce the latency of the video [12]. D2D pairing is essential while choosing a D2D communication because it takes much more time to select the closest devices [13]. So first, check the one-hop relationship and pair those two devices connected in the one-hop relationship [14]. Author [15] used the D2D communication to better video quality by satisfying the QoE requirements. The clustering is carried out when the user needs a D2D communication [16]. It is helpful to get a high-quality video and saves time compared to normal D2D communication [17]. Clustering has a small number of devices, so D2D pairing is easy and reduces latency [18]. For clustering FCM (Fuzzy C Means) algorithm is used. This algorithm is used to cluster the nearest devices, but it does not have an initial point for clustering; it is a cluster in a random manner [19] [20]. Fig 1 represents the general architecture of video streaming in a 5G wireless network. The 5G users are streaming the videos over the internet. The edge devices are used to reduce latency during video streaming, and D2D communication is used to enhance the quality of the videos. The video server is used to maintain all the videos from the 5G users.

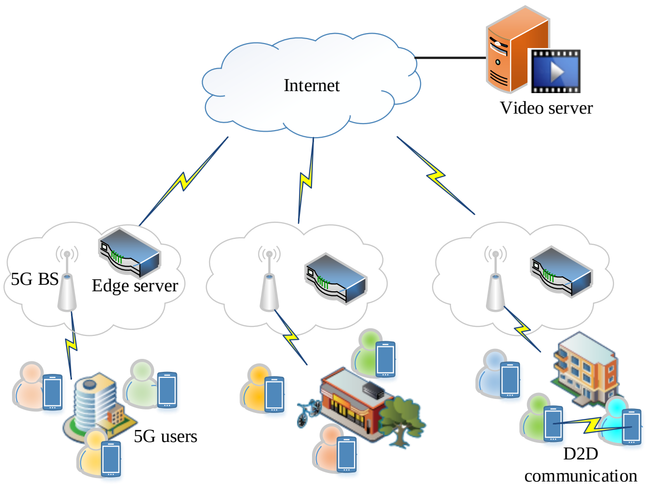

Fig.1 video streaming in 5G wireless network

A. Research Aim and Objectives

Our main aim is to design the Conv-BDN (Convolution Deep Belief Network) with adaptive bitrate control in the video transmission in the 5G wireless networks by using RL(Reinforcement Learning) with Mobile edge computing (MEC) and D2D communication. This paper's scope is to reduce latency and congestion avoidance and improve the QoE performance during video streaming over the 5G wireless network. There have many issues that exist in video streaming in 5G. Because 5G covers a large area, many possibilities exist, such as low latency, packet loss, and congestion problems. For example, existing systems that use a single edge cannot tolerate much data since edge node requires load balancing, congestion avoidance, and packet loss. It also improves the QoE performance. The objectives of our proposed work are discussed as follows

- To provide the best QoE performance to the user during the video streaming in a 5G wireless network by using Conv-DBN architecture. Furthermore, to enhance the video quality by adaptive bit rate in the mechanism of reinforcement learning by using H.266 algorithm is manage the luma and Chroma values.
- To reduce the latency, the task offloading mechanism is used by a delay-based task distribution algorithm.
- To select the multipath in the 5G wireless network to reduce the latency and bandwidth consumption.
- To manage the quality of the video and fast transmission is performed by using virtual clustering in D2D communication.

B. Research contribution

In this paper, we proposed a novel method for video streaming in 5G wireless networks. The significant contribution of this research is listed as follows,

- First, we proposed high-quality based video encoding for enhancing the quality of the videos. In our work, we used H.266 algorithm for improving video quality by considering luma and chroma factors (ex., Resolution, color, and brightness). For this purpose, we proposed a Conv-DBN-based h.266 video encoding technique which reduces the bandwidth consumption.
- Second, we proposed an adaptive bitrate changing method that adaptively changed the bitrate during video streaming. For this purpose, we proposed an A3C algorithm under deep reinforcement learning that automatically learns the environment and changes the bitrate based on the current state.
- Third, we proposed multipath selection for video streaming. The source node selects the best path for streaming the video. We used the best fitness-based equilibrium optimizer algorithm that determines the optimal approach for video streaming. The source node considers buffer size for choosing the optimal path, link stability, distance, energy, and delay.
- Fourth, we proposed task offloading to reduce latency and overload. If the edge is overloaded, then the task will offload to another advantage to avoid congestion. A delay-based task distribution algorithm is proposed for offloading by considering latency, congestion rate, high bitrate video count, and bandwidth utilization, reducing congestion and high bandwidth consumption.
- Finally, we proposed D2D based virtual clustering for improving the quality of the video. Virtual clusters are deployed when a user needs D2D communication. For that, we presented the Advance FCM algorithm. D2D pair is generated based on the link stability, distance, direction, local density, and one hop relationship.

The performance of the proposed work is evaluated using various performance metrics such as throughput, latency, cluster purity, energy consumption, path fitness, PSNR, MOS, and packet loss rate.

C. Paper Organization

The structure of the paper is organized as follows; Section II presents the related works published in video streaming in 5G wireless network. Section III describes the significant problems which are existed in the previous works. Section IV illustrates the proposed system methodologies with algorithm, pseudocode, and equations. Section V demonstrates the experimental results of our proposed work to evaluate the efficiency of our proposed work by comparing many existing system methods. Finally, section VI illustrates the conclusion and future work, concluding the paper by showing the efficiency of video streaming over 5G wireless networks.

II. LITERATURE SURVEY

Paper [21] performs video streaming using DASH (Dynamic Adaptive Streaming over HTTP) over the network with a cognitive mobile edge computing server. This paper consists of four processes. The first is to make a framework of cognitive MEC (Mobile Edge Computing) in a 5G core network. The second one is cache management problem is solved by using dynamic programming. The third one is Pre cached management. This problem is overcome by using a heuristic algorithm. The fourth is selecting the MEC server prototype on the OAI (Open Air Interface) LTE platform. However, This paper does not implement mobility management because mobility management is the essential factor in the performance of cache management. Many edge servers are used here but do not focus on the offloading concept, but offloading reduces the high latency and congestion problems.

Author [22] proposed a short QT partitioning algorithm based on a deep convolutional neural network (CNN) model to predict the coding unit (CU) with H.266/FVC. This paper performs fast intra-coding by using a partition decision algorithm for H.266/FVC. This paper proposes a deep CNN structure to optimize intra-mode QT partitioning decisions. For fast intra-coding, use the binary tree and quadtree. The proposed algorithm achieves a better encoding time performance compared with JEM 7.0 software. However, this paper's intra-prediction model is not implemented, so it takes a long latency to partition the code units. Author [23] focused on reducing the energy and latency by using joint Wi-Fi and cellular network with the mobile edges offloading concept. Each Wi-Fi and base station is connected with the remote cloud server. Mobile terminals cover both Wi-Fi and cellular networks. For Wi-Fi and cellular network, the offloading is performed by using an alternating optimization algorithm. This is being strategic guidance for computation tasks offloading without repeat optimization algorithm execution. Limitations: Here, only consider Wi-Fi and cellular networks, so other network tasks are not performed offloading. So other network video streaming takes a high latency. The balance factor was fixed previously, so it cannot tolerate while exceeding the balance factor range.

Author [24] proposed a cross-layer optimization technique in multi-radio wireless Mesh networks using MDC (multiple distribution coding). This work computes numerous paths using the Passive Interference and Delay Aware (PIDA) metric and performs load balancing using MDC. And also, it is implemented using Ad hoc On-demand Multipath Distance Vector (AOMDV) routing protocol in the NS2 simulator. The proposed work has four steps that are 1. MDC splitter, 2. Congestion monitoring 3. Computation of multiple paths 4. MDC streams forwarding and MDC stream merger. The results are evaluated by using PSNR, frame delay, and frame loss. Limitation: For congestion, monitoring considers only the link stability parameters, so it is not efficient. This paper is not focused on load balancing. And investigate the dynamic channel assignment. The main objective of this paper [25] is to reduce energy consumption and improve the quality of experience (QoE) by using SDMN (Software Defined Mobile Network) combined with MEC (Mobile Edge Caching). The deep reinforcement learning (DRL) algorithm solves the MDP (Markov decision problem). The proposed system achieves the goals successfully, such as energy-saving and QoE enhancement. Here, a virtual cache is created when the computation resource is high.

Limitation: A single mobile edge is used for virtual cache, so congestion will occur while many users need a cache. The paper [26] focused on QoE awareness in cellular networks using DASH (Dynamic Adaptive Streaming over HTTP) based on D2D communication. The QoE has three understandings: the first is cellular resource allocation, the second is caching of video segments, and the third is SM-assignment optimization. The proposed QoE awareness technique achieves the proposed QoE aThe goal in terms of video streaming QoE metrics. Author [27] aimed at developing an algorithm to enhance video streaming over wireless local area networks using a bio cooperative video-aware QoS-based multi-objective cross-layer optimization (MO-CLD) approach. To solve the optimization problem, used bio-inspired optimization algorithm. This algorithm is used to optimize the source rate, packet loss. The goals are achieved successfully based on video quality, end-to-end delay, and buffer queue size. Limitation: Here, video streaming considers only the local network, not the global or wide area. This paper does not investigate the hybrid multi-objective cross-layer optimization for wireless multimedia communication.

Scalable video transmission is proposed in this paper [28] for cache-aided D2D communication. The nearest D2D transmitter is selected for transmitting the video. Initially, the device sends a request to the nearest neighbor. After receiving the request, the closest node sends a response to the node for D2D pairing. This paper evaluates the multiple transmitter selection methods in the content retrieval process to improve the probability, that the cached video can be successfully delivered to the user. CADR parameter is considered for evaluating the performance. The simulation result shows that the proposed method achieves better performance than other state-of-the-art works. However, a scalable video coding method is used here for video transmission since it has low-quality video and consumes high bandwidth. Author [29] proposed QoE modeling for streaming ultra HD videos over 5G networks. The proposed video QoE system utilizes a pair of virtualized network agents within the architecture of SELFNET based mobile edge network architecture. The proposed architecture has three sensors such as flow sensor, video sensor, and resource sensor. Flow sensor monitors every video flow in the 5G network; here, video is encoded using the H.265 encoding algorithm. Then the video sensor extracts the encoded video for each video coding layer. Resource sensor monitors the resources like bandwidth in the network. Finally, this system achieves high accuracy in estimating the QoE values. However, this work used the H.265 video encoding standard, which consumes high bandwidth, increasing resource wastage. Author [30] proposed a scalable virtual network for real-time video transmission in 5G networks. H.265 video coding standard is used for encoding the video. Kernel space-based video processing is proposed to achieve high performance. The load balancer sends video traffic to the virtual optimizer to reduce the congestions during video transmission. The simulation result shows that the proposed work achieves high performance in terms of scalability and flexibility. Limitation: This work used H.265 video coding standard, which consumes high bandwidth compared to H.266, thus increasing resource wastage.

[31] proposed the optimal video streaming method using D2D communication for a dense 5G network. The proposed system considers two scenarios: the first is that video is not available in the network, and the base station delivers the video. The second video already captured the video segment, base station, and GoH showed the video. Here, the scalable extension of higher video coding technique is used to achieve high quality: the proposed system explained source rate distortion, video packetization, and end-to-end reconstructed distortion. By using the D2D communication, the proposed method achieves high PSNR and high-quality video. Paper [32] presented a social aware caching and resource sharing (SCS) for enhancing video delivering capability in 5G ultra-dense networks. This proposed system solves the SCS problem using the D2D communication considered by target SINR for assuring their QoS. Set of the social relationship of D2D communication provides the highest video delivering capability. The simulation result shows that the proposed system achieves high video delivering capacity compared to other existing methods.

III. PROBLEM STATEMENT

Author [33] proposed video streaming by using mobile edge computing technology through the cache server. The cache is used for providing storage and computation resource for adaptive bitrate (ABR). The significant problems of this paper are defined as follows,

- When using a single cache, the congestion rate is high, and it leads to centralized failure.
- Generally, the cache is small in size, and it causes a latency problem when we store lots of videos in a cache server.
- OIGA algorithm is failed to find the globally optimal solution because it does not consider all environment information. Hence bitrate adaptation has not been efficient.

Research Solutions:(1). In our work, we have multiple edges to store and serve the video. So latency is reducing. (2). Here, we are using numerous edges for storing and serving the purpose; it has ample storage, so latency becomes reduced. (3). A3C algorithm is used to solve the problems of the globally optimal solution. This algorithm considers all environment information. (4). A3c consider the parameters of time, bandwidth, and energy to change bitrate adaptively

In paper [34], video streaming is performed by using Edge computing. The deep reinforcement learning (DRL) algorithm develops an automatic algorithm to perform the computational resource assignment and video quality adaptation without prior knowledge of channel statistics. The main problems of this research are listed as follows,

- Here, the edge is a centralized server is always a drawback because all the sources access the same edge it may occur a long latency. Moreover, the centralized server cannot perform a heavy task simultaneously, so load unbalancing and congestion problems arise.
- Using deep reinforcement learning, which doesn't have domain knowledge, didn't choose a specific DRL algorithm for particular environmental learning (smart city, real-time video conferencing).
- In this paper, the DNN network is used to get the optimal solution, but it doesn't have a pre-defined weight of the path. So, it takes too much iteration to find the optimal solution.

Research Solutions: (1). Our Proposed work has multiple edges and agencies to reduce latency because multiple advantages perform numerous tasks simultaneously. (2). Solve the load unbalancing we are using an offloading method. This is used for offloading a scheme to reduce the latency by using a delay-based task distribution algorithm with latency, congestion rate, bandwidth utilization, and high bitrate video count. (3). Here, to solve the domain knowledge problem, we use an A3C algorithm because the A3c algorithm contains more knowledge of diversified training data that will have an environmental action for any scenario.

Author [35] proposed video streaming using the HEVC screen content coding video transmission in wireless networks. H.265machine learning standard is used for video coding. The significant problems of this research are discussed as follows,

- Machine learning leads to high possibility error and increased time and space consumption. Further, it only supports a small amount of data.
- For video coding, H.265 standard is used. It also consumes 50% of the bandwidth for processing video encoding and decoding. Compression and decompression are in different formats, so few videos are transcoded, so the video quality is low. H.265 consumes more resources (Energy, Bandwidth) in mobile devices. It does not focus on in-loop filtering for video quality improvement (Resolution, Brightness, and random noise).

Research solutions: (1). Deep learning does not have any pre-defined data's so it has ample space. (2). For video encoding, the Conv-DBN-based h.266 encoding technique in h.266 standard in loop filter video coding improves the video's color and brightness. (3). Conv-DBN contains pre-defined weight for a path to reduce latency and optimal solution (4). H.266 standard is used in the proposed system saves 50% bandwidth consumption and bitrate, ensuring the same quality of h.265. bandwidth and time are also saved. Moreover, H.266 reduces 50% data requirement compared to h.265. Compression and decompression are in the same format, so many videos are transcoded, so the video quality is high.

Author [36] proposed a scalable video coding standard through preference-aware multipath. MPTCP (Multipath TCP) is used to implement the link preference. The significant problems of this work are discussed as follows,

- Here many sources are select the same path it causes latency and load unbalancing and finds the shortest route takes more iterations, so bandwidth consumption is high. Also, packet loss is high.
- This paper consists of only two networks, such as WIFI and cellular networks; hence it supports only these two networks, which is unsuitable for other network users. And other network users cannot transmit their videos using these networks, thus reducing the process's performance.

Research Solutions: (1). For selecting multipath using a Best fitness-based equilibrium optimizer. In this algorithm, find the shortest path, so iterations are less bandwidth consumption is also low. (2). This algorithm considers buffer size, link stability, distance, energy, delay to find a fitness value. (3). Our proposed work has many WIFI, cellular network, Edge computing, LTE, so any source can transmit their videos using this multipath. (4). Our system has Conv-DBN; it gives a high-quality video it overcomes the low quality in no skip-based streaming.

Author [37] delivered the video in a 5G ultra-dense network based on mobility similarity using D2D communication. One hop D2D pair relationship is used to control the mobility management of the user. The main problems of this research are as follows,

- Many devices are nearer in the correlation process. Still, it takes only two devices at a time, so the searching process for pairing takes a high latency and high bandwidth usage, which increases resource wastage.
- This paper does not investigate the mobility management that often needs frequent device pairing, which reduces the performance of D2D communication.
- Clustering only takes a geographical distance and time, so it is inefficient for clustering, reducing accuracy.

Research Solutions: (1). Our proposed work forms a virtual cluster using Optimum D2D pairing via virtual clustering for pairing a D2D algorithm. HereD2D compares many devices at a time. (2). The Advanced FCM is used for clustering the nodes. Because advanced FCM has an initial selection device, find an optimal path within a short iteration rather than random selection. (3). The cluster is formed by using the parameters of local density, one hop relation, link stability, distance, direction

IV. PROPOSED WORK

Our work has overwhelmed the problems encountered in the existing video transmission in a cross-layer-based 5G multi-RAT wireless network. Our proposed comprises many 5G base stations, LTE, Wi-Fi, cellular network, multiple edges, and D2D. We have five processes: video encoding, adaptive bitrate changing, multipath selection, task offloading, and D2D based virtual clustering. These processes are explained in figure 2. These processes are discussed as follows

A. High Quality Based Video Encoding

In our work, video encoding is performed by using high-definition video coding standard H.266. This standard video coding concentrates the quality of the video by using the luma and chroma factors such as Resolution, color, and brightness. For this purpose, we have employed Conv-DBN (Convolution Deep Belief Neural Network) based h.266 video encoding technique. This reduces bandwidth consumption and data requirements. Here, video compression is performed by the h.266 encoding algorithm. A faster video transmission encoding algorithm consumes 50% less bandwidth than H.265 without compromising quality. Generally, 10 gigabytes of data takes 9min to transmit UHD video. But H.266 takes 9min to transfer 5 gigabytes of data at the same rate. Hence it consumes less bandwidth compared to others. For image compression, we used Conv-DBN deep learning method for reducing the compression time. Initially, the encoder consists of the number of units equivalent to the color of the images. The first layer of Conv-DBN is convolution layers that encoded the image using the h.266 encoding algorithm. Then, encoded images are sent to the probabilistic max pool layer. Next, a fully connected layer decodes the images using H.266 coding algorithm. Then the fully connected layer delivers the decoded or output images.

$$X(F) = [cbdn(f1), cbdn(f2), \ldots\ldots cbc \qquad (1)$$

The encoded frames of each video are compressed and delivered for further process. Finally, it calculates the loss between original and reconstructed images. The Conv-DBN algorithm takes less time to compress the data, which increases the efficiency of the video coding process. Passing the video frames has the advantage of fast training rather than sending a whole video to the network. Intra frame compression is performed for video compression.

Algorithm: High Quality based Video Encoding
1. Specify several units for input videos
2. Initialize Conv-DBN
3. Repeat
4. Image encoding process
5. $F \leftarrow$ video frames for encoding
6. CL$\leftarrow$Image encoding by H.266 at convolution layer
7. ML$\leftarrow$Forward encoded image to probabilistic

max pool layer(CL)
8. FL ← Image decoding completed at fully connected layer using H.266
9. Until image decoding is completed for each frame in the video

B. Adaptive Bitrate Changing

We have performed the adaptive bitrate changing during the video streaming. This adaptive changing method is used to improve the video quality by considering the parameters such as video priority level and SLA constraints. We are changing the adaptive bitrate by using the A3C algorithm under Deep Reinforcement Learning (DRL). The A3C agent consists of two parts: the actor process and the critic process. The actor process defines parameterized policy and generates actions based on the observed states.

In contrast, the critic process evaluates and criticizes the current approach by processing the reward obtained from the environment. The proposed algorithm comprises three elements, namely state (, action ( ), and reward ( ). The state represents current environment information such as channel quality, video quality, and buffer. The action denotes the change in the bitrate adaptively to achieve QoE. The reward is the improved variation in video quality and buffering time. The Q function to earn better reward can be computed as,

$$Q^{\pi}(\varsigma,\forall) \approx \mathcal{R}' + \varepsilon C^{\pi}(\varsigma') \approx \mathcal{R}' + \quad (2)$$

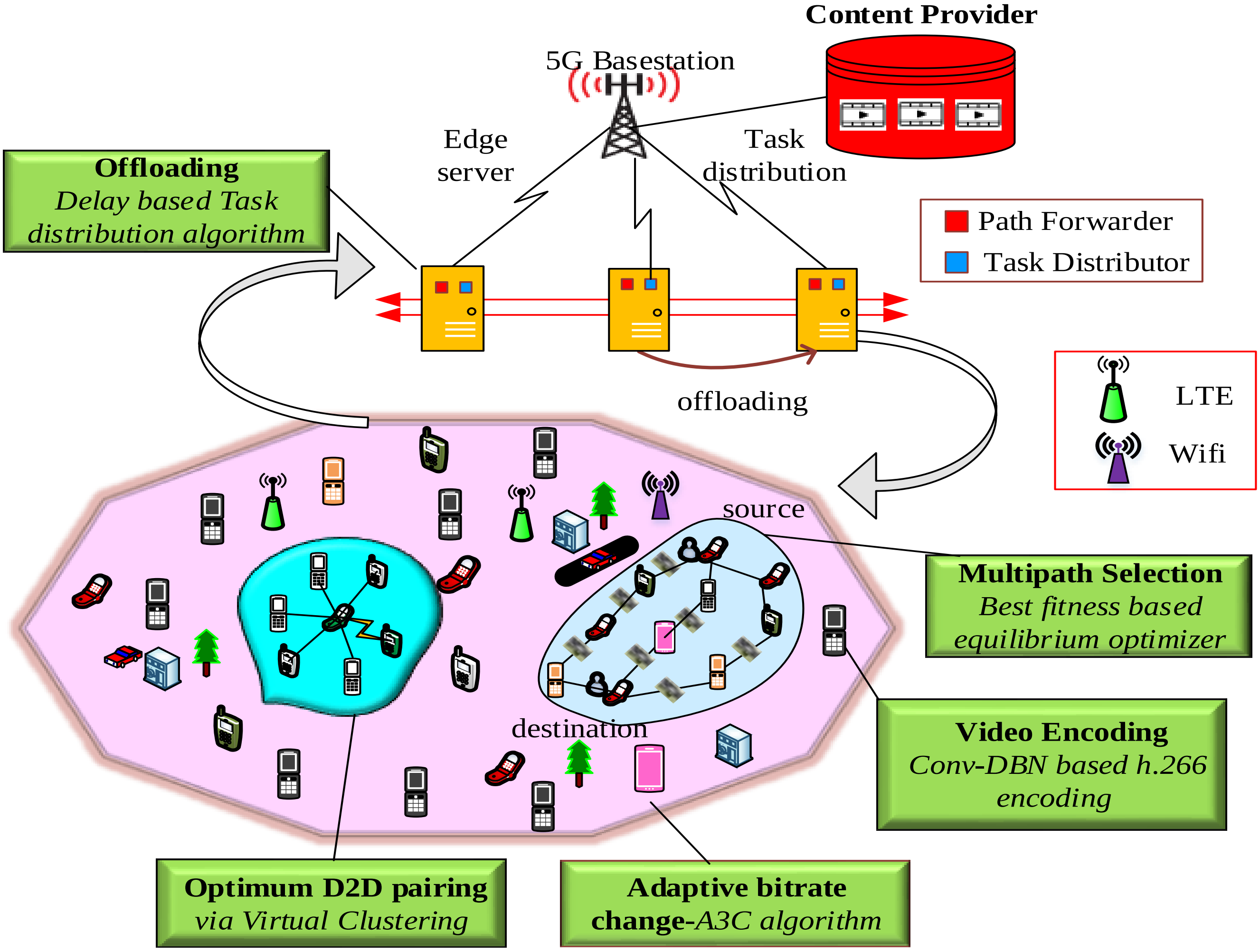

Fig.2 Proposed video streaming architecture

Where denotes the policy of the actor-critic network, denotes the critic with the parameter as . For the Q function, the corresponding advantage function can be formulated as,

$$A^{\pi}(\varsigma,\forall) = Q^{\pi}(\varsigma,\forall) - C^{\pi}(\varsigma') \approx \mathcal{R}' + \varepsilon C^{\pi}_{\phi}(\varsigma') - C^{\pi}_{\phi} \quad (3)$$

The target computation in each step transition can be represented as,

(4)

The gradient computation of critic can be computed as,

(5)

Where denote the discount factor and denotes the critic loss function, which can be expressed as

$$L_c = \frac{1}{\beta}\Sigma_{ST} \quad (6)$$

Where represent the batch size and represents the respective state transition. The actor gradient is computed by,

$$\nabla^{actor} = \frac{1}{\beta}\Sigma_{ST}\, \nabla_\theta \log \pi_\theta (\quad (7)$$

Both actor and critic gradient summation is computed for each state transition, thereby achieving the policy. This facilitates the dynamic adaptation of bitrate to achieve QoE in the network.

C. Multipath Selection

In a 5G wireless network, many sources perform video streaming. These videos are transmitted from source to destination. Many paths are presented between the source and destination. The source device selects the best approach for streaming their videos. For this purpose Best fitness-based equilibrium optimizer algorithm is used. This algorithm considers the parameters such as buffer size, link stability, distance, energy, and delay for selecting an optimal path. These five parameters are used to find the fitness value of an optimal approach. Initially, the population initialization is carried out to begin the optimization, which can be formulated as,

$$P_k^{initial} = P_{min} + rand_k(P_{max} - P_{min}),\ k = 1,2,. \quad (8)$$

Where represents the initial concentration, is the quantity of particle, and Represents the random vector. The equilibrium among the paths is computed to converge to the optimal way. The set of equilibrium participants is constructed, which can be expressed as,

$$\vec{P}_{q\_set} = \{\vec{P}_{q(1)}, \vec{P}_{q(2)}, \vec{P}_{q(3)}, \vec{P}_{q(4} \quad (9)$$

The updation of concentration is continued until the optimal path is determined, which the participants will carry out. The update process is performed with the help of exponential term which can be formulated as,

(10)

Where is denoted turnover rate, which varies from 0 to 1? The time can be formulated concerning the iterations,

$$\tau = \left(1 - \frac{current_{iter}}{max_{\ iter}}\right)^{(b_2} \quad (11)$$

Where denotes the current iteration and Denotes the maximum number of iterations. The exploitation capability of the proposed optimization algorithm is managed by the constant . The exploration capability can be represented as,

$$\vec{\tau}_0 = \frac{1}{\vec{\mu}}\ln(-b_1 sign(\vec{r} - 0.5)[1 - e^{-\vec{\mu}} \quad (12)$$

Where the exploration capability is controlled by the constant .then eqn(10) can be rewritten as,

$$\vec{E} = b_1 sign(\vec{r} - 0 \quad (13)$$

The exploitation process is influenced by the factor named generation rate, which can be formulated as,

(14)

Where denote the initial value, which can be represented as

$$\overline{G_1} \quad (15)$$

$$\overrightarrow{PGr} = \quad (16)$$

Where, and take the value between 0 and 1 randomly and Denotes the contribution of generic terms for updating, and represents the probability of assistance. The rule of updation can be defined as,

$$\vec{P} = \vec{P}_q + (\vec{P} - \vec{P}_q).\vec{E}\cdot \quad (17)$$

The second term improves the exploration phase, and the accuracy of the solution is enhanced by the third term, thereby improving the exploitation phase. The memory saving function contributes to achieving better fitness value. The pseudocode of the proposed path selection algorithm is presented below,

Pseudocode: Best fitness-based equilibrium optimizer
Population initialization k=1, 2, …n
Initialize input parameters ; ; ;
While <
For k=1: number of paths
Calculate fitness of path
If
Replace with and with
Elseif > & <
Replace with and with
Elseif > & < & <
Replace with and with
Elseif > & < & <
& <
Replace with and with
End (If)
End (For)
$\vec{P}_{q(avg)} = \vec{P}_{q(1)} + \vec{P}_{q(2)} + \vec{P}_{q(3)} + \vec{P}_{q(4)}/4$
Construct using Eqn (9)
Perform memory saving (if > 1)
Compute from Eqn (11)
For k=1: number of paths (k)
Select one participant from in a random manner
Generate and
Compute using Eqn (13)
Compute using Eqn (16)
Compute using Eqn (15)
Compute using Eqn (14)
Perform updation using Eqn (17)
End (For)
=
End While

D. Task Offloading

In our proposed work task offloading process is performed to reduce the latency and load unbalance. Many sources are choosing the same path at a time it may occur latency and congestion. To avoid these problems, we are using multiple edges. The edges are used for storing and serving the videos. If any latency has occurred, then the edge performs the task offloading, which means the task is distributed to another advantage; it prevents the unbalancing load problem and congestion avoidance problem. For this purpose, we are using Delay Based Task Distribution Algorithm. This algorithm considers parameters such as latency (L), congestion rate (CR), high bitrate video count (VC), and bandwidth utilization (B). It saves bandwidth and time also. Initially, the category of the task is to be identified based on the parameters into two classes, namely sensitive and non-sensitive, which can be formulated as,

$$T_c = \begin{cases} sensitive & , if\ D < Th\ and\ ETTL \\ non-sensitive & , if\ D \geq Th\ and\ ETTL \end{cases} \quad (18)$$

Where denotes the task category, deadline, threshold, and estimated time to live, respectively. The edge server tasks identify the task category of the scheme is maintained in the respective queue. The weight of each task is computed in order to rank the tasks in the queue for the purpose of effective offloading. The weight computation can be formulated as,

$$T_w = \frac{(w_1 \times L) + (w_2 \times CR) + (w_3 \times VC) +}{4} \quad (19)$$

Where Denotes the weight value of the task. The task's priority depends on the weight value in which the tasks having lower weight value have higher priority. If two tasks have the same weight, then the size of the functions is considered for offloading. The selection of servers is carried out based on the load, distance, and CPU utilization. For instance, the server with the lowest CPU utilization is selected if the task is categorized as sensitive. If there are multiple servers with equal CPU utilization, then the server's load and distance are considered for effective server selection. By doing so, the offloading of delay-sensitive tasks are performed effectively.

E. D2D Based Virtual clustering

In our proposed work performs a Device Device communication for improving the quality of the video. D2D pairing means the direct transmission of the devices without any intermediate. For D2D pairing, we first design a virtual clustering which means the cluster appears only the user needs a D2D communication. Here, Advanced FCM (advanced Fuzzy C Means) clustering is used to make a virtual clustering. The cluster forming is based on the local density. Finding the closest points between the devices, if it is minimum, will be paired for D2D communication. For D2D communication, the following parameters consider link stability, distance, direction, local density, and a one-hop relationship.

In this paper, virtual clustering is formed by certain constraints, and the devices that contain the pairing request messages are included in the virtual clusters. We proposed an advanced fuzzy c means algorithm for virtual clustering, which creates a group based on distance and local density. The objective function of advanced fuzzy c means is defined as follows,

$$I(u, v, p) = \sum_{j=1}^{n} \sum \quad (20)$$

Where represent the local density from the ith center of the jth sample and Represent distance and represent the membership function. Advanced FCM generates multiple clustering centers which are similar, but local density is different for every cluster. We calculate the correlation between the clusters if the cluster has a higher density with less distance, cluster devices are selected for D2D pairing. A node with a higher transmission rate and lesser latency-based devices is used for communication. However, it's highly challenging to tackle the stability and efficiency issues under a large-scale environment, and the separate utility function is defined using the transmission rate and latency for pairing policy verification to request or send data between the devices. In the following, we formulate the transmission rate based utility function for the requested device,

$$\cup_i (t) = \begin{cases} r_i(\delta) \\ 0, & (\end{cases} \quad (21)$$

Where represents the indicator function, and if the device meets the condition, the value is one; otherwise, 0. Then we formulate the latency based utility function for the requested devices

$$\cup_i (L) = \begin{cases} l_i(\delta) & if \delta\ (\\ 0, & Oth \end{cases} \quad (22)$$

Where Represent the indicator function of latency.

$$\cup_i (\hbar) = \{\cup_i (t) \quad (23)$$

Finally, we calculate the utility function. If the device meets the utility function's condition, it will be considered for D2D pairing.

V. EXPERIMENTAL STUDY

The experimentation of the proposed A3C-DBVS model is performed with extensive simulations. The experimental study includes three sub-sections: simulation setup, comparative analysis, and research summary for the proposed system rather than the existing system.

A. Simulation Study

The proposed A3C-DBVS model is evaluated by the NS3.26 network simulator, which supports all the 5G wireless network specifications. The proposed dynamic bitrate for the video streaming method is considered a simulation environment for testing video streaming in 5G wireless networks. The system configuration is presented in table 1. And table 2 illustrates the simulation parameters

TABLE.1 System Configurations

Software configuration	OS	Ubuntu 14.04 LTS
	Network Simulator	NS3.26
Hardware configuration	RAM	4GB
	Processor	Pentium Dual-core and above
	Hard Disk	60GB

.

TABLE.2 Simulation parameters and their descriptions

Parameters	Descriptions
Node speed (max)	5 m/sec
Simulation area	$800m \times 1000m$
No. of 5G base station	1
No. of the edge server	5
No. of eNodeB	2
No. of the access point	2
No. of user nodes	100
Video coding standard	H.266
Simulation time	10000ms
Round duration	20000ms
Range of transmission	250m
Buffer size of the node	64 packet
No. of flows	50
No. of frames per video	350
Packet carrying duration	500 to 1000ms
Type of traffic	UDP, TCP
Weighting time for neighbor nodes	300ms
Propagation delay	Random
Forwarding capacity	2Mbps
Mobility model	Random
Type of queue	Priority-based queue
Type of interface	Physical wireless
Distribution of nodes	Random

B. Comparative Analysis

This section describes the evaluation of the proposed A3C-DBVs model in terms of various metrics. The proposed A3C-DBVS model compared with existing models, in particular, we considered the following performance metrics as throughput vs. no. of devices, latency vs. no. of devices, bandwidth utilization vs. no. of devices, Goodput vs. no. of devices, jitter vs. no. of devices, Energy consumption vs. no. of devices and no. of edges, path fitness vs. no. of paths and PSNR vs. no. of devices, Mean opinion score vs. no. of devices, packet loss rate vs. no. of devices.

a) Impact of Throughput

Throughput represents the successful rate of videos are delivered from source to destination in a specific time over a 5G wireless network.

(24)

Where represents throughput and represents the number of videos delivered from source to destination. Represent the time taken by the video provided to the destination over the network.

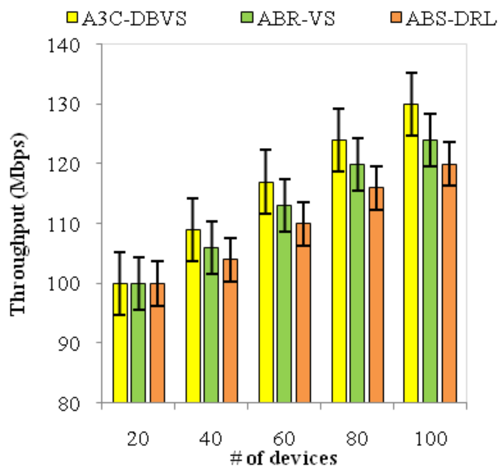

Fig.3 Throughput vs. No. of devices

Fig 3 compares the proposed A3C-DBVS model and the existing model's throughput concerning the number of devices. The fig clearly states that the proposed A3C-DBVS model achieves high throughput compared to current works. Because we used H.266video coding standard to enhance video quality and the bitrates are adaptively changed during video streaming, increasing video quality. And we select an optimal path for forwarding the video from source to destination using the best fitness-based equilibrium optimizer algorithm that chooses the optimal path from multiple pathways, thus increasing the success rate. In this way, we achieve high throughput compared to existing systems. Table 3 illustrates the numerical analysis of throughput. It represents the average values of proposed and existing model throughput concerning the number of devices.

TABLE 3 Throughput (Mbps) Analysis

Method	No. of. devices
A3C-DBVS	116 5.0
ABR-VS	83.17 5.0
ABS-DRL	89.02 5.0

b) Impact of latency

This metric is used to measure the latency of video streaming. It represented the additional time the video transmitted from source to destination due to congestion, weak stability between paths, etc. The latency is calculated as follows,

(25)

In other words, latency represents the difference between completion time and expected time. Where L represents the latency and represents the completion time, and Represents the expected time.

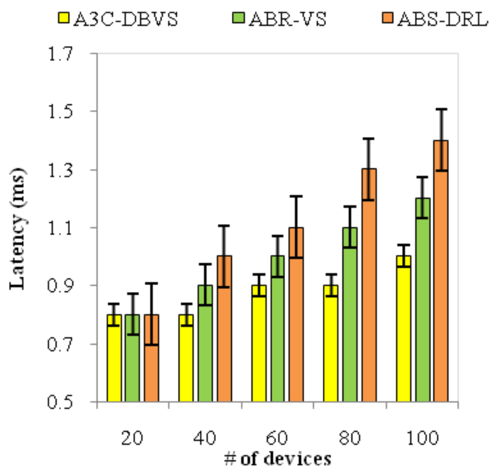

Fig.4 Latency vs. No. of devices

Fig 4 represents the comparison of proposed and existing model latency concerning the number of devices. The fig states that the proposed system takes less time to transmit the video from source to destination over the 5G wireless network. The proposed A3C-DBVS model achieves low latency compared to other models because we select the optimal path from multiple paths for video streaming. The optimal approach is determined based on the buffer size, link stability, distance, energy, and delay, reducing latency. Optimal path selection reduces latency instead of selecting a random path because an unexpected approach may cause congestion, long-distance, and weak stability. Large buffer size leads to latency, and hence our method takes less time to transmit the video from source to destination. Table 4 illustrates the numerical analysis of latency. That represents the comparison of proposed and existing model latency, showing that the proposed A3C-DBVS model achieves low latency than existing models.

TABLE 4 Latency (ms) Analysis

Method	No. of. devices
A3C-DBVS	0.88 0.05
ABR-VS	1 0.05
ABS-DRL	1.12 0.05

c) Impact of Energy Consumption

This metric is used to calculate the energy consumed by the video transmitted from source to destination. Energy consumption increase reduces the performance of the devices because of the resource constraint nature of the devices. Energy consumption is calculated as follows,

(26)

In other words, energy consumption states the difference between initial and residual energy. Where represent energy consumption and represent initial energy and Represent residual energy.

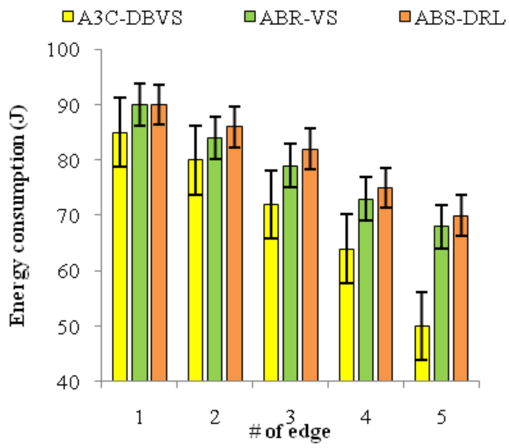

Fig. 5a Energy Consumption vs. No. of edges

Fig 5a represents the comparison of the proposed and existing model's energy consumption concerning number edges. The comparison result shows that the proposed A3C-DBVS model consumes less energy compared to the existing system. Furthermore, our work used the H.266 video coding standard to enhance the quality, which consumes less bandwidth and power than H.265 without compromising the video quality. And we select an optimal path for video streaming instead of random selection, which reduces path selection latency and reduces energy consumption. Finally, we used D2D communication for video streaming, reducing energy consumption because communicating two devices directly without any intermediate device, thus reducing energy consumption and increasing video quality. In this way, our method consumes less energy than the existing methods such as ABR-VS and ABS-DRL. Table 5 illustrates the numerical analysis of energy consumption for both proposed and existing systems, showing that the proposed A3C-DBVS model consumed less energy than others.

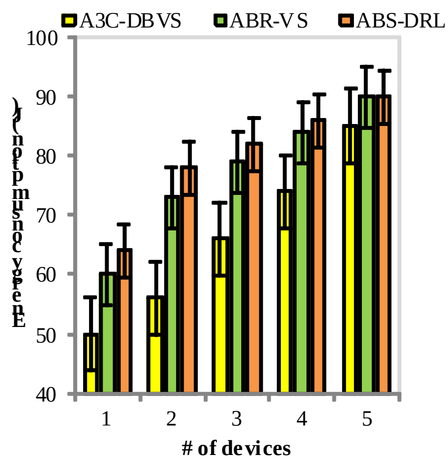

Fig. 5b Energy Consumption vs. No. of devices

Fig 5b represents the comparison of energy consumption for both proposed and existing models concerning the number of devices. The energy consumption is increased exponentially with the increasing number of devices. The result shows that the proposed A3C-DBVS model consumes less energy compared to the current works. The energy consumption is reduced by selecting the optimal path and using D2D communication.

TABLE 5 Energy Consumption (J) Analysis

Method	No. of. edge	No. of. devices
A3C-DBVS	70.2 1.0	66.2 1.0
ABR-VS	78.8 1.0	72.2 1.0
ABS-DRL	80.6 1.0	80.0 1.0

d) Impact of Bandwidth Utilization

This metric measures the bandwidth utilized by the devices during video transmission over 5G wireless networks. In other words, bandwidth utilization is stated that the difference between total bandwidth and residual bandwidth. The bandwidth utilization is defined as follows,

(27)

Where BU represents bandwidth utilization and represent total bandwidth and Represent residual bandwidth.

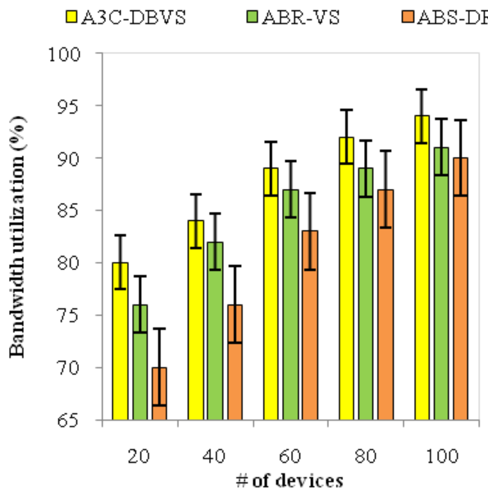

Fig. 6 Bandwidth utilization and number of devices

Fig 6 represents the comparison of bandwidth utilization of proposed and existing models concerning the number of devices. The figure shows that the proposed system achieves high bandwidth utilization compared to existing systems. Our work proposed an H.266 encoding standard for encoding the video during video streaming, which consumes 50% less bandwidth than the H.265 and H.264 video coding standard without compromising quality. We change the bitrate adaptively, thus reducing waiting for time and that increase bandwidth utilization. But existing works do not modify the bitrate adaptively, thus increasing high bandwidth utilization. And our work selects the optimal path from multiple paths that increase bandwidth utilization rather than select random paths. We increase bandwidth utilization by performing Virtual D2D clustering, multipath selection, task offloading, and adaptive bitrate changing. Table 6illustrates the numerical analysis of bandwidth consumption that shows that the proposed method utilizes high bandwidth.

TABLE 6 Bandwidth Utilization (%) Analysis

Method	No. of. devices
A3C-DBVS	87.8 0.5
ABR-VS	85.0 0.5
ABS-DRL	81.2 0.5

e) Impact of Path Fitness

This metric is used to evaluate the path fitness for reducing packet loss during video streaming. The path fitness is measured based on the link stability, distance, energy, buffer size, and delay. Path fitness is increased by considering these parameters.

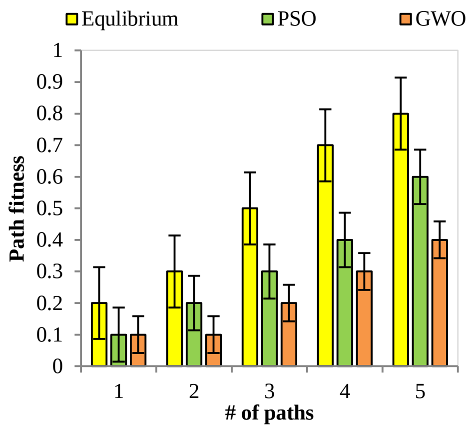

Fig. 7 Path fitness vs. No. of paths

Fig 7 represents the comparison of path fitness for both proposed and existing path selection mechanisms. The figure shows that the proposed system achieves high path fitness compared to an existing PSO and GWO. Our proposed equilibrium method considers link stability, distance, energy, buffer size, and delay for calculating the fitness of path that increases path fitness. But the existing approach does not consider these parameters; hence it achieves less fitness and does not select the optimal path that increases packet loss rate. And the current methods PSO and GWO have low convergence rates; hence, it takes much time to determine optimal paths that increase latency. Our proposed equilibrium method has high convergence that takes less time to choose an optimal path, improving the performance of path selection and reducing latency.

Table 7 illustrates the numerical analysis of path fitness for both proposed and existing path selection mechanisms. The result shows that the proposed equilibrium method achieves high path fitness, reduces packet loss rate, and increases video quality.

TABLE 7 Path Fitness Analysis

Method	No. of. devices
Equilibrium	0.5 0.05
PSO	0.32 0.05
GWO	0.22 0.05

f) Impact of PSNR

This metric is used to calculate the video compression quality. And it is computing the value of MSE between the sending and receiving video chunks.

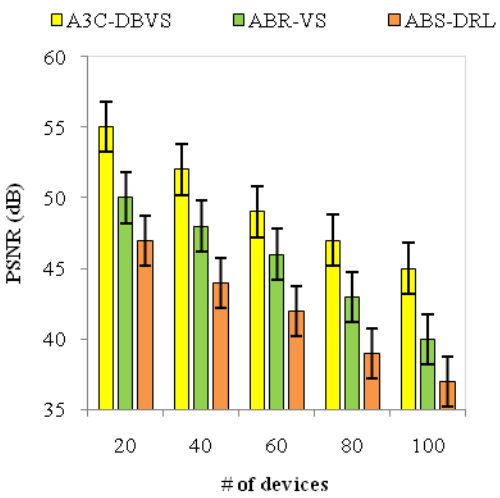

Fig.8 PSNR vs. No. of devices

Fig.8 represents the comparison of proposed and existing PSNR values concerning the number of devices. The fig clearly states that the proposed A3C-DBVS model achieves a high PSNR value compared to existing works. Because our work used the H.266 video coding standard to enhance the quality of the video, which provides high quality even large amount of devices, we select an optimal path between source and destination for video transmission, thus reducing packet loss, increasing PSNR values. Table 8 illustrates the numerical analysis of PSNR, which shows that the proposed A3C-DBVS model achieves high PSNR compared to the other two models.

TABLE 8 PSNR (dB) Analysis

Method	No. of. devices
A3C-DBVS	49.6 1.0
ABR-VS	45.4 1.0
ABS-DRL	41.8 1.0

g) Impact of Mean of Score

This metric is used to evaluate the quality of the video packets. It is one of the significant metrics which is assessed based on the experience of users.

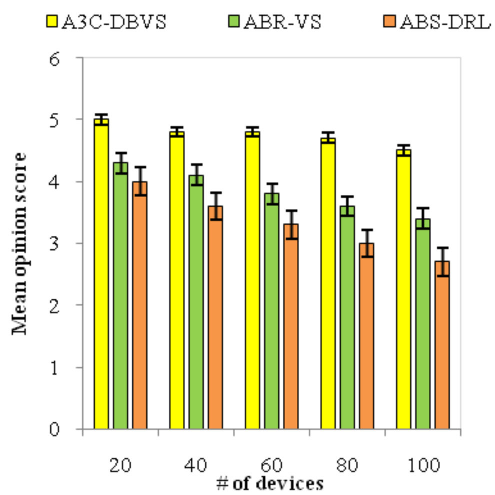

Fig.9 Mean Opinion Score vs. No. of devices

Fig.9 represents the comparison of proposed and existing Mean Opinion Score (MOS) concerning the number of devices. MOS is used to measure the efficiency of the proposed A3C-DBVS model. This research used the H.266 video encoding method that provides high-quality video compared to the existing H.255 video coding standard. And we proposed a virtual clustering D2D method that increases video quality due to direct communication instead of communicating via a third party. And we select the optimal path between source to destination, thus increase the efficiency of video streaming due to reducing the packet loss. In this way, we achieve high MOS compared to existing works. Table 8 illustrates the average values of the MOS for both proposed and existing models concerning the number of devices. The numerical analysis shows that the proposed A3C-DBVS model achieves high MOS values.

TABLE 8 Mean Opinion Score Analysis

Method	No. of. devices
A3C-DBVS	4.76 0.05
ABR-VS	3.84 0.05
ABS-DRL	3.32 0.05

h) Impact of Packet Loss Rate

This metric is used to evaluate the packet loss rate during video transmission from source to destination. Packet loss is occurring due to high congestion and ineffective selection of a path from multiple paths.

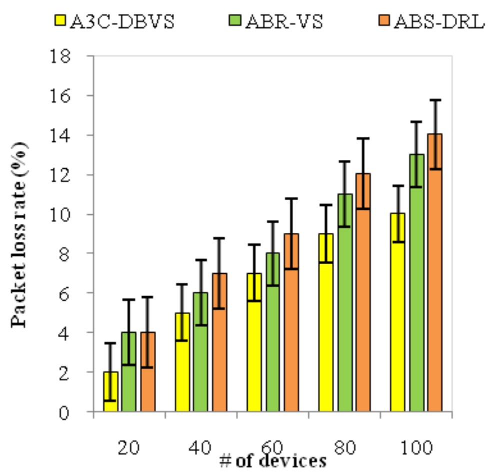

Fig.10 Packet loss rate vs. No. of devices

Fig.10 represents the comparison of proposed A3C-DBVS and existing ABR-Vs and ABS-DRL models concerning energy consumption concerning the number of devices. The figure states that the proposed model achieves less packet loss compared to existing models. Because the proposed model selects an optimal path from multiple paths thus reduces packet loss. The optimal way has low congestion and high stability. The minimum distance between source and destination thus reduces packet loss rate. We consider buffer size, link stability, distance, energy, and delay to select optimal paths from multiple paths for path selection. And we proposed D2D communication between two devices without any intermediate devices, which reduces packet loss compared to other systems. Table 9 illustrates the numerical analysis of the packet loss rate for both proposed and existing models. The numerical analysis shows that the proposed approach achieves less packet loss rate compared to the existing models.

TABLE 9 Packet Drop Rate (%) Analysis

Method	No. of. devices
A3C-DBVS	6.6 0.5
ABR-VS	8.4 0.5
ABS-DRL	9.2 0.5

i) Impact of Goodput

Goodput is an application-based metric that states the number of bits transmitted from source to destination in a specific amount of time through a 5G wireless network. Generally, Goodput is affected by three metrics such as overhead, packet retransmission, and high congestion.

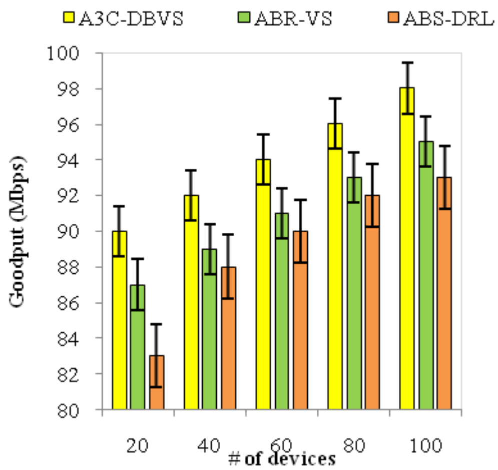

Fig.11 Goodput vs. No. of devices

Fig 11 represents the comparison of Goodput for both proposed and existing methods concerning the number of devices. The figure shows that the proposed method achieves high throughput compared to current works. Our work selects an optimal path to reduce high congestion, overhead, packet loss, and packet retransmission, thus increasing Goodput compared to existing models. Path selection considered a delay, congestion, buffer size, and link stability, thus increasing Goodput due to reducing congestion and retransmission. In our work, task offloading is performed to reduce overhead and latency, which is also used to improve Goodput. Table 10 illustrates the numerical analysis of Goodput for both proposed and existing models. It shows the average values of Goodput.

TABLE 10 Goodput (Mbps) Analysis

Method	No. of. devices
A3C-DBVS	94 2.0
ABR-VS	91 2.0
ABS-DRL	89.2 2.0

j) Impact of Jitter

Jitter is used to measure the time difference between packet transmission and reception during video streaming over a 5G wireless network.

(28)

Where J represents the jitter and represent the packer transmission and Represent packet reception. Fig. Represents the comparison of jitter for both proposed and existing models concerning the number of devices. The comparison result shows that the proposed system achieves low jitter compared to the other two existing models. The multipath selection is presented in our work, reducing transmission delay due to lowering congestion and overhead over the path. And D2D communication is proposed to reduce the transmission delay by avoiding intermediate devices, thus reduces jitter. And tasks are offloaded if the path is overload, reducing transmission delay and increasing jitter compared to others.

TABLE 11 Jitter (%) Analysis

Method	No. of. devices
A3C-DBVS	1.08 0.05
ABR-VS	1.14 0.05
ABS-DRL	1.26 0.05

Table 11 illustrates the numerical analysis of jitter that shows that the proposed method achieves low jitter compared to existing models.

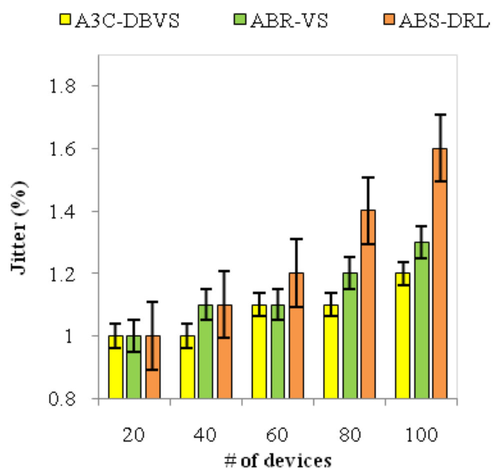

Fig.12 Jitter vs. No. of devices

C. Research Summary

This section explains how the proposed system has improved the performance compared to the existing system. Fig.3-11 describes the implementation of the proposed scheme in terms of throughput, latency, energy consumption, path fitness, jitter, Goodput, bandwidth utilization, PSNR, MOS, and packet loss rate. The performance is achieved by proposed high-quality-based video encoding, adaptive bitrate changing, task offloading, multipath selection, and virtual-based D2D clustering methods for video streaming in a 5G wireless network. The research highlights are discussed as follows,

- Our work utilized the H.266 video encoding, which provides a better video quality and consumes low bandwidth.
- In our work, we have adaptively change the bitrate by using environmental factors such as throughput and noise. A3C algorithm changes the bitrate, which absorbs the environment actions and reacts to the corresponding response. This is used to improve the quality of the video.
- Our work has multiple edges to perform the task offloading to balance the load and reduce latency by using a delay-based task distribution algorithm.
- Our work chooses multipath by using the best fitness-based equilibrium optimizer, which is selecting the optimal path. Furthermore, it reduces packet loss and latency by considering link stability, bandwidth consumption, and more.
- In our work, virtual clustering is created for D2D communication by using the Advanced FCM algorithm. It reduces the latency and provides a high-quality video because it does not contain any intermediate devices.

VI. CONCLUSION AND FUTURE WORK

In this paper, the A3C-DBVS method is proposed for video streaming in a 5G wireless network to achieve high video quality and reduce congestion between the path from source to destination. Firstly, high-quality-based video encoding is proposed to enhance the quality of videos and reduce bandwidth utilization using the Conv-DBN-based H.266 encoding technique. Secondly, the bitrates are adaptively changed based on the environment. Therefore, we proposed an A3C algorithm that automatically learns the background and updates the bitrate based on the current status, increasing video quality. Thirdly, the best paths are selected from multiple pathways using the best fitness-based equilibrium optimizer algorithm to avoid high congestion and high latency during video streaming. Then we proposed task offloading for reducing latency and overload during video streaming. For that purpose, the proposed system used multiple edges to perform offload. Finally, virtual-based D2D clustering is performed to stream video from one device to another without any intermediate devices, thus reducing latency and increasing video quality. Finally, simulation is conducted and proved that the proposed system achieves better performance compared to existing systems. In the future, we plan to integrate a blockchain for enhancing security during video streaming in 5G wireless networks.

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