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Impact of Wireless Network Packet Loss on Real-Time Video Streaming Application: A Comparative Study of H.265 and H.266 Codecs

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Abstract: The transmission of real-time videos over wireless networks is prone to the negative consequences of packet loss and delay, which can have a potential effect on the video quality during streaming. These impairments can lead to interruptions, buffering, and degradation of visual and auditory elements, resulting in an unsatisfactory user experience. In this paper, we aim to address the challenges associated with packet loss and delay parameters in wireless networks and propose an approach to alleviate their impact on real-time video transmission. The proposed approach involves utilizing the H.265/H.266 video coding standards. For Versatile Video Coding (VVC), a patch support for VVdeC and VVenC to Fast Forward Moving Picture Expert Group (FFmpeg) is added. As a result, FFmpeg is used to encode, stream and decode all videos. Raw video for both slow and high motion with 2K resolution is used, maintaining a consistent frame rate of 50 fps and a bit-rate of 20 Mbps. The streamed videos are encoded based on the adaptive quantization for the above-mentioned codecs. By selecting optimal transmission data based on various network conditions, this approach enhances the quality of experience for end-users while minimizing resource usage in the wireless network. Furthermore, the proposed approach selects the codec standards according to their bit-rates and frame rates. Simulation results indicate that the proposed approach has a significant improvement for real-time video streaming over wireless networks to satisfy the end user experience. Simulation results indicates that the Peak Signal-to-Noise Ratio (PSNR) values for H.265 and H.266 are (33.66 dB and 32.58 dB) and (28.45 dB and 27.13 dB) for the low and high motion videos respectively. The approach also outperforms other related work by gaining a PSNR of +12 dB for H.265 and +13 dB for H.266 when the network packet loss is 1%.

1. Introduction

The rapid increase in the demand for video streaming services has experienced significant expansion in recent years. This growth is driven by the widespread availability of high-speed internet, the proliferation of mobile devices, and the rising popularity of on-demand entertainment. Multimedia streaming has become a critical service for many hybrid Wired and Wireless networks that offer IP services, especially in live, real-time, and Video on Demand (VOD) streaming. Currently, video streaming services and IP traffic transmission via wireless networks are experiencing notable enhancements, and they are projected to account for a significant 82% of total internet traffic consumption by the end of 2023. As a result, the importance of real-time video streaming is expected to increase, representing approximately 13% of internet video traffic by the end of 2023 [1, 2].

The video codecs H.264/ Advance Video Coding (AVC), H.265/High-Efficiency Video Coding (HEVC), and H.266/Versatile Video Coding (VVC) are widely utilized across various applications. H.264, also known as AVC, has been the dominant codec for years, providing excellent compression efficiency. H.265, or HEVC, offers significant improvements in compression efficiency but requires more computational power. H.266, also referred to as VVC, is the latest standard, offering even greater compression efficiency than its predecessors. Due to its superior performance, H.266 is considered the preferred choice for applications requiring high-quality video streaming and optimal bandwidth usage [3]. However, network delays and packet loss significantly impact video streaming quality, posing a major challenge.

As the demand for video streaming services grows, the transmission of video streams over networks becomes increasingly susceptible to various network issues. Delay, the time taken for data packets to travel from their source to their destination, and packet loss, where some packets fail to reach their destination, both contribute to this problem. Additionally, increased delay can cause synchronization issues between audio and video components, leading to a noticeable decline in overall quality.

Several strategies have been explored to address these challenges, with some focusing on optimizing video streaming and others on improving network performance. To counteract quality degradation due to congestion, two main approaches are used: open-loop and closed-loop congestion control. In the open-loop method, the router and end system operate independently, following policies such as acknowledgment, admission, retransmission, selective repeat, and discard. The closed-loop method deals with congestion after it occurs, with the congested node notifying upstream nodes, the sender, and the receiver of the congestion [4]. The Khandu *et al.* [5] chose to focus on the H.264 and H.265 video codec standards in their study due to their widespread use and market dominance in various applications, including mobile services, videoconferencing, and HD/UHD video storage. Although H.266 has been introduced, its lengthy encoding time and high computational demands led the authors to concentrate on H.264 and H.265. The study employs learning approaches to minimize prediction error rates when video frames are dropped.

Efficient architectures, protocols, and scheduling mechanisms are developed by analyzing the traffic characteristics of various Virtual Reality (VR) applications. The study computes a theoretical background on throughput requirements for an optimal VR experience and examines traffic characteristics using a Wi-Fi network. The findings provide valuable insights into the development of advanced optimization algorithms, access mechanisms, protocols, and scheduling algorithms in the VR field [6]. A new method for real-time traffic shaping in 5G- vehicular ad hoc networks is introduced using distributed reinforcement learning. This method investigates the impact of adjusting coding parameters on achieving optimal traffic rates for high-quality streaming. The proposed techniques improve Quality of Experience (QoE) using the objective Peak Signal-to-Noise Ratio (PSNR) metric and reduce frame latency [7].

This paper presents a comparative study evaluating the quality of experience (QoE) of video streaming using the H.264, H.265, and H.266 codec standards in wireless networks. The proposed framework considers various parameters, including video characteristics (bit-rates, frame rates), Quality of Service (QoS), and end-user QoE using both subjective, Mean Opinion Score (MOS), and objective, PSNR and Structural Similarity Index Measure (SSIM) quality assessments. To improve QoE for end users in wireless environments, an adaptive quantization parameter approach is used. This approach aims to minimize negative effects by selecting the most suitable quantization parameter values. The contributions of this study are as follows:

- Encoding raw videos (high and slow motion) for 2K resolution using Fast Forward Moving Picture Expert Group (FFmpeg) integrated with Versatile Video Coding (VVC) and streaming them over the wireless network.
- Investigation of network parameters such as packet loss, which impacts the QoE of video streaming applications.
- Selection of the codec type (H.265 and H.266) for streaming based on video bit-rates and frame rates.

- Identification of optimal quantization parameter values to reduce any artifacts that may affect end-user satisfaction.
- Conducting comprehensive objective quality evaluations to ensure that end-user QoE requirements are met.

The remainder of this paper is structured as follows: section 2 reviews the latest advancements in high-quality video standards within video streaming over wireless networks. Section 3 details the system and algorithm methodology. Section 4 describes the system testbed used in this study. Section 5 presents the experimental setup and evaluation of test results. Finally, section 6 concludes and suggests potential future research directions.

2. Related Work

This section provides an in-depth survey of recent studies that examine the evaluation of QoE for video file streaming, specifically focusing on codec standards H.264, H265, and H.266 respectively. The work explores the impact of QoS traffic parameters in wireless networks, such as packet loss, and network delay on the QoE using subjective and objective quality metrics. Additionally, the effect of parameters involved in video compression including frame rates, resolution, and quantization parameters, is thoroughly discussed.

Tadeus *et al.* [8] introduced a large-scale study with MPEG video codec's family and compared each other by using QoE and User Experience (UX) feedback. They analyzed codec advantages, disadvantages, and developed practical QoS models based on protocol analysis by taking into consideration the packet loss and burst factor. They provided an accurate QoE prediction for improved user satisfaction [8]. Currently, the exponential growth of Multimedia IoT tools and devices, which generate a significant amount of data with diverse properties and requirements are serious challenges. This growth has led to the development and deployment of AI-based multimedia IoT systems for many video services, such as HD and UHD video surveillance and mobile multimedia streaming. Soulef *et al.* [9] proposed a novel technique called wide-activated squeeze-and-excitation deep convolutional neural network (WSE-DCNN) for enhancing video quality in VVC. By replacing conventional in-loop filtering, the approach reduces compression artifacts, leading to improved visual quality. Results reveal notable Bjøntegaard Delta (BD) rate reduction and superior performance in comparison with the conventional CNN filter-based methods. Experimental results show that the proposed model reaches the significant compression rate when objective and subjective qualities are measured with a saving of BD rate of about -2:85%, -8:89%, and -10:05% for Y, U, and V channels, respectively.

In real-time scenarios, the video data is transmitted over IP networks, which use Real-time Transport Protocol (RTP) protocol instead of unreliable User Datagram Protocol (UDP). For instance, video conferencing, live-streaming, and videotelephony are often subjected to the deterioration caused by various sources. The most significant is the impact of video coding and its transmission over wireless communication channels. Juraj *et al.* [10] aimed to investigate the effect of packet loss rate (PLR) on video quality in full HD and ultra-HD resolutions encoded with H.264 and H.265 formats. They compiled a dataset of 11,200 test video sequences with varying parameters and simulated PLR. Objective evaluation using PSNR and SSIM metrics, as well as subjective evaluation using the Absolute Category Rating (ACR) method, were conducted. The results showed a close correlation among assessment methods, but MOS provided more insights for combining the effect of PLR and compression.

Various approaching of streaming protocols in wire and wireless networks have been introduced, which are described as important components of network backbone. Big Packet Protocol (BPP), which is a network protocol, is designed for future applications of networking architecture. Stuart *et al.* [11] introduced novel methods and techniques for transmitting video layers using Scalable Video Coding (SVC) and the Packet Wash mechanism of the BPP. BPP is designed to handle high-bandwidth, low-latency applications and allows a dynamic adaptation of packets during transmission. By eliminating specific chunks, rather than dropping or retrying packets, BPP reduces payload and packet size. They evaluated the performance and compared it with UDP and transmission control protocol (TCP) approaches. Their main contributions included mapping SVC video into BPP packets for low delay and low packet loss delivery, providing better QoE result than UDP or TCP. This approach enhances video streaming performance, ensuring continuous delivery and guaranteed quality even in limited bandwidth environments. VVC, which is considered the newest codec standard, was deployed in July 2020. It was implemented by the Joint Video Experts Team (JVET) of the ITU-T Video Coding Experts Group (VCEG). The aim was to reduce the compression ratio of video while preserving the quality of the video and supporting a broader range of media content and leading-edge technologies. Bross et al. [12] presented an intensive overview of the new techniques and applications with features that achieve high bit-rate reductions near of 50% and 75% over its predecessor HEVC and AVC standards for the same video quality respectively. They described how these new features in VVC give higher versatility for applications. Powerful applications of these standards are high dynamic range video, an ultralow-delay streaming, high-resolution video beyond the standard, a 360◦ immersive video, and multilayer coding. The VVC standard provides a remarkable reduction of bit-rate of about 50% while maintaining subjective quality compared to its previous one, HEVC. Although VVC is still developed to support chipsets and devices. Adam *et al.* [13] introduced an open-source software packages that enables the creation of a full VVC toolchain for end-to-end streaming. The packages include the VVenC library for efficient VVC encoding and the VVdeC library for live decoding. VVC is also integrated into project of advanced content (GPAC) software tools and the FFmpeg media framework that allows packaging of VVC bitstreams in the MP4 file format using the Dynamic Adaptive Streaming over HTTP (DASH) protocol.

Currently, the growth rate of digital video in proliferation media services has made a vital requirement for accurate and high-speed coding, streaming, and decoding algorithms. Marko *et al.* [14] presented the first publicly end-to-end pipeline for live 4K30p VVC intra coding and streaming. It comprises three open-source parts: (1) uvg266 for encoding VVC files, (2) uvgRTP for streaming VVC files, and (3) OpenVVC for decoding VVC files. The prototype demonstrates the proof of the setup's capabilities, which has a fast performance of almost 34,000 times than the same pipeline using the VTM codec. These findings highlight the prototype as the sole viable open-source solution for live 4K VVC intra coding and streaming. With the deployment of recent Ultra High-Definition Television technology, the QoE of end-users is anticipated to enhance when new features are introduced to the pre-existing HDTV system, which includes high frame rates, high dynamic range, higher spatial resolutions, and wider color gamut with 4K (3840 × 2160) and 8K (7680 × 4320) [15]. Charles *et al.* [16] conducted a robust statistical analysis using rate-distortion (RD) curves, BD rate evaluation, and a student's t-test to compare VVC and HEVC for 8K video files. Objective evaluations using PSNR, MS-SSIM, and VMAF metrics revealed VVC's bit-rate gains of 31%, 26%, and 35%, respectively. Subjectively, VVC reduced bit-rate by 41% while maintaining visual quality, with some sequences achieving a 50% compression gain.

Shang *et al.* [17] proposed a new framework for video live streaming, particularly for the transmission of low and high-motion content such as movie action and sports events. The quality of real and live streaming video is widely impressed by many facts, including distortions occurred during the coding, decoding, data delivery, and artifacts. As a result, an efficient algorithm of the objective quality evaluation that can judge the quality perception of dynamic motion, and live streamed video is highly demanded. For this purpose, they made a video-based quality database specially developed for live streaming research. The database contains 315 videos of 45 different sources from 33 original packings damaged by 6 distortion types.

Different Testbeds have recently been developed and designed for an adaptive video streaming including server for encoding videos, wireless networks for streaming videos, and client for decoding and playback videos. Taha *et al.* [18] proposed a virtualized network testbed that supports the implementation of an adaptive video streaming with QoE metrics, including initial delay, frequency switches, accumulative video time, CPU usage, and battery energy consumption. Moreover, the impact of QoS parameters on the above-mentioned metrics for various segment lengths is studied. Test results indicate that the proposed virtualized Testbed is easy to install, use and cost effective than real testbeds. In addition, the subjective performance evaluation reveals that the optimal segment lengths of 6 to 8 seconds were selected to satisfying the end-users.

Recently, Taha *et al.* [19] introduced a smart algorithm based on adaptive quantization for video streaming in wireless network environments. The method constructs a relationship between the Quantization Parameter (QP) in H.264 and H.265 codec standards and the QoS of 5G wireless technology.

Packet loss of 5G wireless network is emulated using NetEm Linux-Based Software to show the impact of QP on the video quality using DMOS and objective quality (PSNR and SSIM) metrics. The proposed framework has assessed the QoE and experiments on slow and high video motions with HD resolution (1920 × 1080).

Malekzadeh *et al.* [20] proposed a two-phase model to enhance mobile video transmission efficiency. Phase 1, Network-Related Settings (NRS), addresses mobile transmission link limits by developing four distinct mobile networks, including LTE, 802.11ax dual-band, and 802.11ac. Phase 2, video-related settings (VRS), focuses on real-time video constraints and utilizes five well-known compression algorithms in the reference video preparation process. This model incorporates various factors impacting the mobile video transmission process. It is implemented, and results assess video delivery efficiency based on network-level quality of service and service-level quality of experience. To validate and refine the model, a testbed was established, with measured experimental results compared to simulations.

Šilić *et al.* [21] conducted research aimed at developing a digital alternative to existing technology. Their study involved two user assessments to evaluate the QoE of a First-Person View (FPV) system integrated with a cloud-based drone flight simulator. The research focused on the impact of various video encoding parameters—such as bit-rate, resolution, and frame rate. Both studies employed a similar methodology but included different participant groups: University students and staff from the University of Zagreb in the first study, and flight students and instructors from the Spanish Air Force Academy in the second. The latter group had prior experience with piloting and flight simulators. The findings indicate that video encoding parameters have a significant effect on perceived QoE, whereas prior piloting experience has a minimal impact on quality ratings.

The core aspects of each study summarized in table 1. which is highlighting the methodologies used, the benefits and limitations of those methodologies.

Table 1: Comparison between recent techniques.

Ref	Technique	Benefit	Weak Point
[8]	QoE and UX feedback, QoS models	Practical QoS models based on protocol analysis	Focuses only on MPEG video codecs
[9]	WSE-DCNN	Reduced compression artifacts, improved visual quality	Limited to VVC
[10]	PSNR, SSIM, ACR methods	Close correlation among assessment methods	MOS provided more insights than PSNR and SSIM
[11]	SVC, Packet Wash mechanism of BPP	Better QoE, continuous delivery in limited bandwidth	Requires mapping SVC video into BPP packets
[12]	VVC standard	Significant bit-rate reduction while maintaining quality	Still under development to support chipsets and devices
[13]	VVenC and VVdeC libraries, GPAC, FFmpeg	Efficient VVC encoding and live decoding	Limited to specific software tools
[14]	uvg266, uvgRTP, OpenVVC	Fast-performing open-source solution for 4K30p VVC	Prototype stage
[16]	Statistical analysis (RD curves, BD rate)	Significant bit-rate gains, visual quality improvements	Limited to 8K video files
[17]	Video-based quality database	Specialized for live streaming research	Limited to specific distortion types
[18]	Virtualized network testbed, adaptive quantization	Cost-effective, easy to install, optimal segment lengths	Limited to HD resolution
[20]	Two-phase model (NRS and VRS)	Efficient mobile video transmission	Limited to specific mobile networks and compression algorithms
[21]	QoE evaluation with FPV system	Significant influence of encoding parameters on QoE	Minor impact of prior piloting experience

Although several researchers have dedicated their efforts to studying the QoE by tuning QoS parameters, the impact of packet loss and network delay on the H.266 codec standard remains unexplored

[22-30]. As a result, this study aims to bridge this research gap and make a significant contribution to the existing literatures. To investigate the effects of QoS parameters on the QoE of VVC standard, a comprehensive case study is conducted. Additionally, in order to enhance the QoE for end-users, an adaptive quantization technique was employed to effectively manage the quality aspects of the streamed video. By addressing this crucial aspect, this research endeavors to offer valuable insights into optimizing the QoE and providing an improved streaming experience for end-users.

3. Materials and Methods

In this section, we detail the materials and methodologies employed in our study, focusing on video codecs and their pivotal role in ensuring efficient, high-quality video streaming over the internet. Given the rising demand for online video content, it is essential to examine advanced video codecs to guarantee optimal video delivery across diverse network conditions. For this method, we utilized a range of state-of-the-art video codecs, including H.264/AVC, VP9, AV1, HEVC (H.265), and VVC (H.266). These codecs were selected due to their widespread use and relevance in current internet streaming environments. The study involved encoding video sequences using these codecs, with each codec's performance evaluated based on various metrics such as compression efficiency, bit-rate savings, and video quality. The methodology followed in this study comprises several key steps:

- **Video Codec Selection:** The selection of video codecs was based on their prominence in the industry and their ability to address the evolving demands of video streaming. H.264/AVC, introduced in 2003, has long been the standard for video compression. It employs techniques such as inter-frame prediction, spatial and temporal prediction, and entropy coding to achieve high compression efficiency. Despite its age, H.264/AVC continues to provide a balanced trade-off between video quality and compression, making it applicable for a broad spectrum of uses.
- **Emerging Codecs Evaluation:** We included newer codecs such as VP9, AV1, HEVC, and VVC in our analysis to assess their potential in addressing the limitations of older codecs like H.264/AVC. VP9, an open-source codec developed by Google, offers improvements in motion estimation, adaptive loop filtering, and entropy coding, leading to better video quality at lower bit-rates. AV1, developed by the Alliance for Open Media, is designed to surpass VP9's compression efficiency by using advanced intra-frame prediction, entropy coding, and motion compensation. The study compared these codecs' performance to establish their suitability for modern streaming applications.
- **Compression Efficiency and Quality Assessment:** The study involved a comprehensive analysis of each codec’s compression efficiency and video quality. HEVC, also known as H.265, was evaluated for its enhanced prediction modes, larger block sizes, and improved entropy coding, which contribute to approximately 50% bit-rate reduction compared to H.264/AVC. Similarly, VVC (H.266), the newest codec, was analyzed for its advanced coding tools, such as improved motion compensation and intra-frame prediction, which significantly reduce bit-rate while maintaining high video quality.
- **Experimental Setup:** The research incorporated an experimental setup where video sequences were encoded using the selected codecs. The encoded videos were then streamed over various network conditions to evaluate the codecs’ performance. Metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) were used to measure video quality, while bit-rate and latency were recorded to assess efficiency.

This methodological approach allows for a thorough comparison of state-of-the-art codecs, offering insights into their effectiveness in modern video streaming scenarios. The findings contribute to the ongoing discourse on optimizing video delivery across increasingly complex network environments.

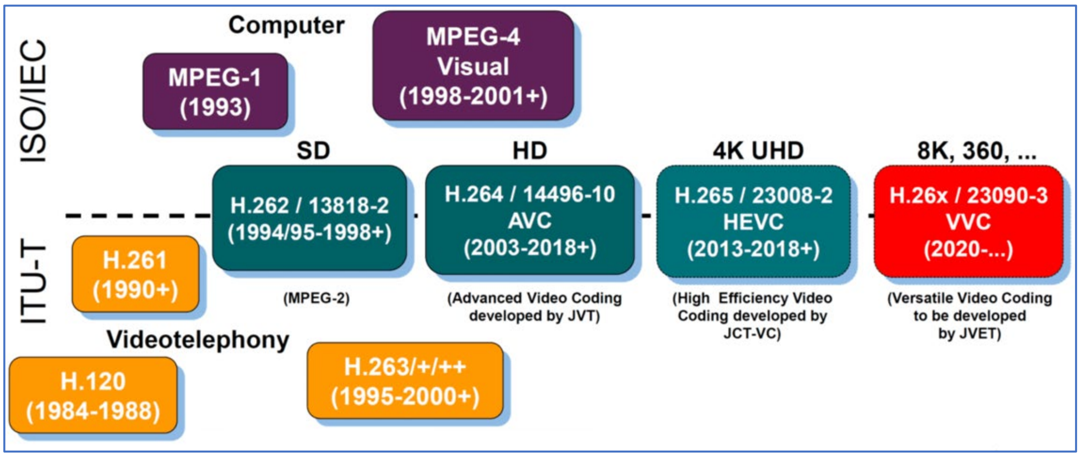


Figure 1: International video codec timeline [31].

In table 2, the importance of codec's parameters of (H.264, H.265, H.266) is shown in terms of compression, network bandwidth, resource utilization, streaming performance, and their usage.

Table 2: Comparison of different codecs.

Parameters	H.264 (AVC)	H.265 (HEVC)	H.266 (VVC)
Compression Efficiency	Good	Significant Improvement	Superior
Computational Resources	Moderate	Higher	Higher than H.265
Bandwidth Utilization	Moderate	Improved	Enhanced
Video Quality	Good	Better	Improved
Compatibility	Widely Supported	Widespread Adoption	Growing Support
Adoption Rate	Established	Increasing	Emerging
Streaming Performance	Efficient	Efficient	More Efficient than H.265
Network Resilience	Moderate	Improved	Enhanced
Encoding Complexity	Moderate	Higher	Higher than H.265
Bit-rate	Scalable ½ MPEG-2	Scalable ½ H.264	Scalable ½ H.265
Usage	QuickTime, DivX	New generation,	Next generation,
	Cable TV, Youtube	4K content	8K

The general block diagram of the proposed system is displayed in figure 2. The methodology of the proposed approach includes as follows:

- **Raw Video Compression:** The process begins with the compression of original video content to facilitate efficient transmission. This is typically achieved through video encoding techniques like H.265 (HEVC) and H.266 (VVC). These codecs reduce the video file's size while preserving a certain level of quality.
- **Determining Bit Rate and Frame Rate:** Before initiating the streaming process, it's essential to determine the appropriate bit rate and frame rate for the video stream. This decision considers several factors, including available network bandwidth and the characteristics of the video content itself. The selection of the optimal bit rate and frame rate is critical to ensure a seamless viewing experience.
- **Codec Selection Optimization:** The system has the flexibility to select between H.265 and H.266, or even a combination of both, based on specific requirements and available resources. Both H.265 and H.266 are advanced video codecs designed to achieve efficient compression while maintaining high video quality. The choice may depend on factors such as device compatibility and network conditions.
- **Wireless Network Video Streaming:** Following video encoding and parameter configuration, the video is streamed over a wireless network. This is typically accomplished using the

UDP, known for its suitability in real-time multimedia streaming due to its low latency. However, it's crucial to recognize that UDP lacks error correction or retransmission capabilities, making it necessary to implement mechanisms for addressing packet loss.

- **Receiving and Decoding:** On the receiving end, a video decoder is employed to receive and decode the streamed video content. The decoder decompresses the video and prepares it for display.
- **QoE Evaluation:** The system conducts an assessment of the QoE delivered by the video stream. This evaluation encompasses various factors such as video quality, playback smoothness, and latency. QoE metrics serve as a means to gauge the satisfaction level of end-users with their viewing experience.
- **Determining User Satisfaction:** Based on the QoE measurements, the system can make determinations regarding the satisfaction of users with the video streaming experience. In instances where the QoE falls below predefined thresholds, adjustments may be necessary. These adjustments could involve reducing the bit rate or frame rate to accommodate varying network conditions or enhancing the encoding quality. This approach ensures that users receive the best possible experience within the constraints of their network environment.

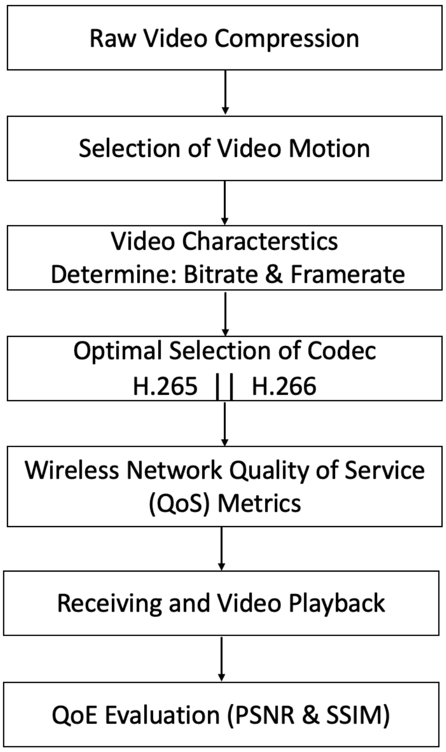


Figure 2: General system blockdiagram.

The upcoming sections offer a thorough analysis of each component in the proposed computational system. This analysis focuses on the architecture, operational dynamics, and connectivity of each module, clarifying their individual roles within the framework. By examining the design, functionality, and interactions of each element, the analysis ensures a clear understanding of how all parts contribute to the system's overall goals.

3.1. Raw Video Samples and Characteristics

Raw videos with a format (y4m) are taken from the link https://media.xiph.org/video/derf/ for both slow and high motion with 2K resolution. Figure 3 shows some frame samples.

(a) Old Town – slow motion – 2K

(b) Crowd Run – high motion – 2K

Figure 3: Frame snapshots of videos.

The video characteristics with the various quality of resolutions are described in table 3.

Table 3: Video characteristics.

Video genre	Size / Frame rate	Bit rate / Mbps	Characteristics
Old Town - 2K	1.45 GB – 50 fps	20	Smooth motion of the camera and static background
Crowd Run – 2K	1.45 GB – 50 fps	20	High motion with abrupt change in human objects

3.2. Encoding Phase

As mentioned in table 2, the file size of raw videos with 10-second length is quite large. Therefore, they must be compressed by several encoders that are used for various applications such as HEVC, and VVC. FFmpeg package provides many libraries that can be utilized, including libx265 for encoding HEVC. In this work, we have integrated the VVC encoder into FFmpeg by adding patch support in order to encode VVC/H.266 video files. Along with the coding libraries, other parameters are involved the preset, which determines compression efficiency and therefore affects the encoding speed. Default preset is medium but it can be ultrafast, superfast, very fast, faster, fast, medium, slow, slower, very slow, and placebo. Moreover, the quantization has a significant impact on the compression rate. QP values from 0 to 17 are acceptable while retaining the visual quality.

3.3. Streaming Process

FFmpeg has also facility to stream encoded videos using different protocols for both live and real-time streaming (UDP, TCP, RTP, RSTP, MPEG-DASH). In this research, the encoded data are streamed using UDP protocol. To simulate the impact of QoS parameters especially network packet loss during the streaming process in the proposed wireless network Testbed on the QoE of end-users, the network emulator Linux-based (NetEm) for traffic control was used.

3.4. Decoding Phase

On the client side, end-users decode the streamed video for playing back and saving with H.265 and H.266 formats respectively.

3.5. End-users QoE Evaluation Metrics

Finally, the streamed and encoded video quality is evaluated using objective QoE metrics (PSNR and SSIM).

3.5.1. PSNR

Is a metric that calculates the ratio between the square of maximum intensity of frame pixels and the noise introduced in the video signal. It is regard as an engineering term and mostly used as a quality measure of video reconstruction [32]. Mean Square Error, which represents the error produced during the video streaming by the effect of QoS parameters. The mathematical representation of PSNR is given in the equation (1).

$$PSNR = 10 * log_{10} \frac{I_{max}^2}{MSE} \quad (1)$$

$$MSE = \frac{1}{MxN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [f(i,j) - g(i,j)]^2 \quad (2)$$

Where f(i,j) represents the encoded video frames for all standards whereas g(i,j) indicates the streamed frames.

3.5.2. SSIM

The human vision system is an important aspect for extracting the structural information of video in term of quality estimation. An important property of SSIM is that it is invariance to light condition compared to PSNR, which is light change dependent. It is range value varies between 0 to 1 where (1) displays the maximum quality while (0) indicates that there is no change between the encoded and streamed video [33]. SSIM contains three components include luminance (intensity of light), color contrast, and structural information as depicted in equation (3).

$$SSIM\ (i,j) = f(I(i,j), c(i,j), s(i,j)) \quad (3)$$

The server plays a critical role in dynamically adjusting video resolution by accounting for variations in bitrate and frame rate, ensuring optimal encoding for both slow-motion and fast-motion sequences. This flexibility is vital for preserving video quality, especially when content dynamics vary. The Quantization Parameter (QP) is precisely calibrated to enhance compression efficiency while maintaining video fidelity during reconstruction. If the selected QP impacts perceived quality, the video is streamed accordingly; otherwise, an alternative QP value is applied to sustain the desired quality.

Simultaneously, the network emulator adjusts Quality of Service (QoS) parameters, with an emphasis on packet loss, to assess their effects on the H.265 and H.266 codec standards. This evaluation is crucial for understanding how these codecs perform under different network conditions, which can greatly affect video transmission quality.

The Quality of Experience (QoE) is then measured using objective criteria such as Peak Sig-nal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) to ensure that the end-user receives satisfactory QoE levels.

Figure 4 shows the system's flowchart, highlighting the sequential interactions between the server, the wireless network, and the clients. During encoding, the server prepares the video data for transmission. The wireless network then manages the streaming process, handling data transfer and adapting to varying network conditions to minimize latency and packet loss. Finally, the clients perform the decoding, converting the received data back into a viewable format. The figure effectively demonstrates the cooperation among these components, ensuring efficient video streaming and maintaining high-quality standards regardless of network fluctuations.

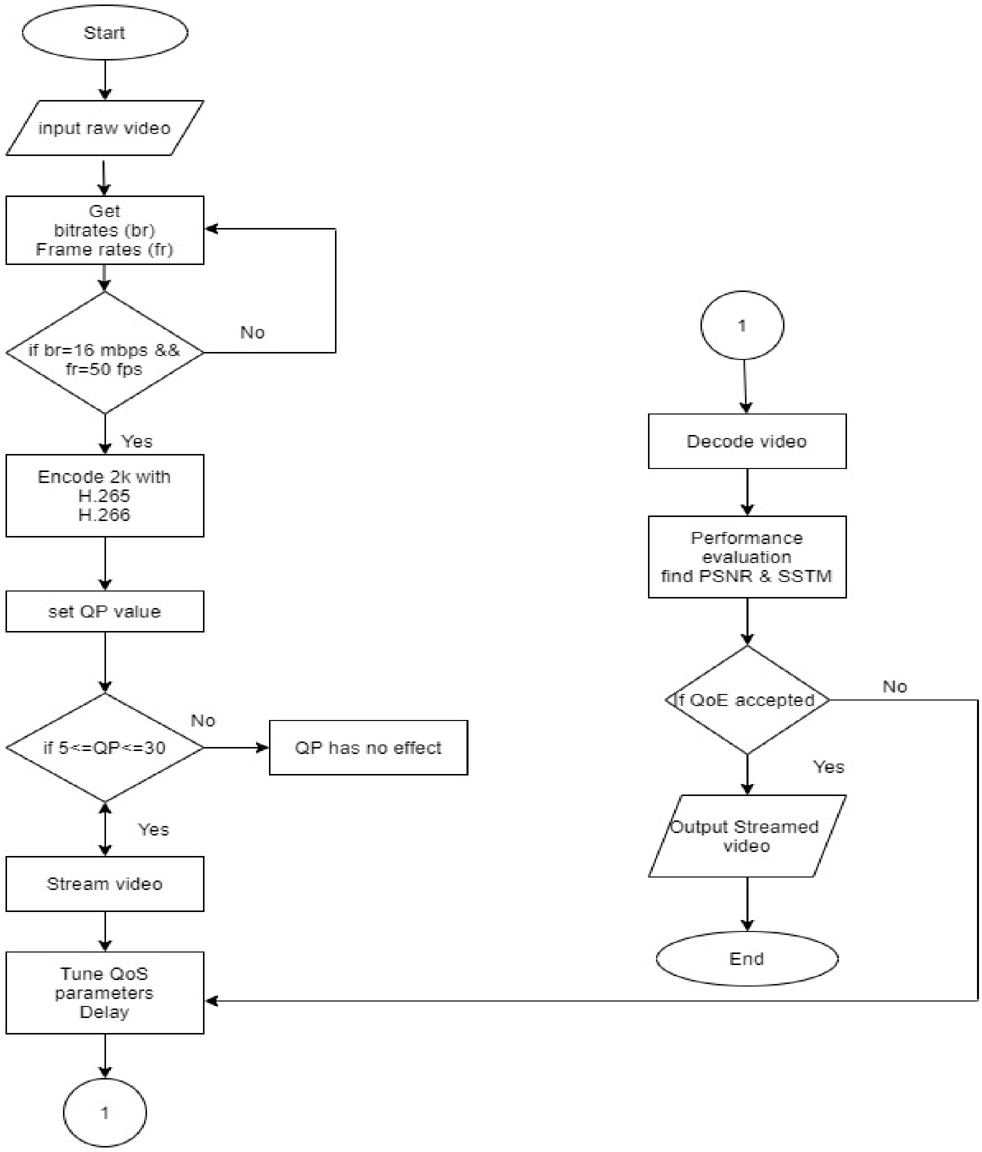


Figure 4: Flowchart of the proposed system.

3.4. Testbed Design

To simulate the experimental tests, an efficient Testbed is provided in a green environment at the University of Sulaimani, designed to accommodate various heterogeneous devices. This setup includes two Linux-based workstations, one for the server side and the other for the client side, a wireless network environment, and multiple smart devices to ensure a comprehensive testing scenario. The network traffic is controlled using the NetEm emulator, which simulates QoS parameters such as delay and packet loss for each QP value, aiming to achieve high-quality streamed videos. UDP is utilized as the transmission protocol, efficiently handling the transfer of H.265 and H.266 data from the server to the clients. Additionally, the proposed Testbed has been implemented and rigorously tested with 4K resolution to evaluate its performance. Figure 5 illustrates the real Testbed setup used in this model.

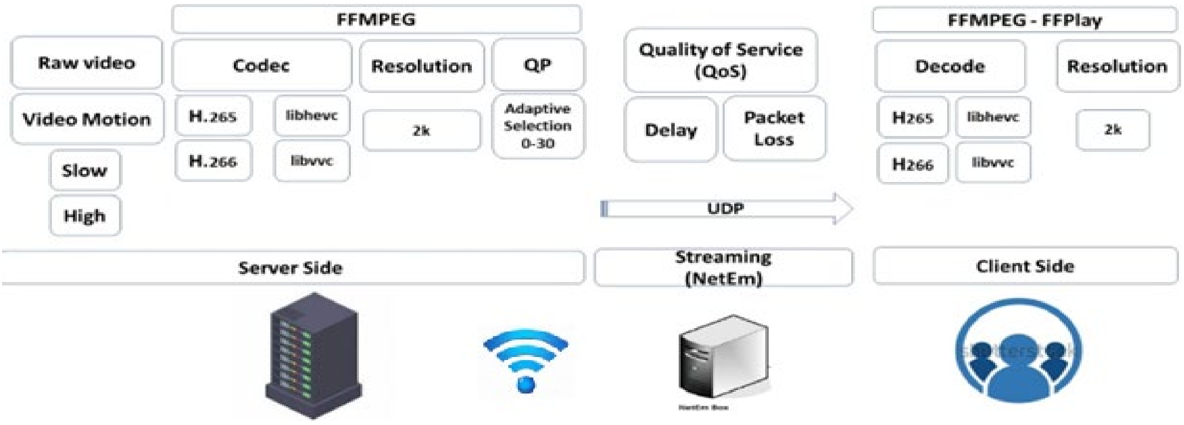


Figure 5: Proposed Testbed implementation.

4. Results

The implemented testbed utilizes two Linux-based workstations, designated for server and client roles. This configuration forms the backbone of our video streaming evaluation. In our rigorous testing regime, we examined the system's performance by subjecting it to two distinct scenarios: one involving low-resolution 2K videos and another with high-resolution 2K content. These tests served to assess how effectively the system handled varying bandwidth requirements and video complexities. The data collected from these experiments yielded critical insights into video quality, latency, bit rate, frame rate, and packet loss, guiding our efforts to enhance the overall streaming experience for users.

4.1. Low Motion Video Results

In table 4, the results of PSNR and SSIM for QP values are presented using H.265 and H.266 codecs. When QP value is 25, the PSNR values are close for the codecs with the compressed video size (H.265 – 3.5 MB) and (H.266 – 2.54 MB), respectively. Therefore, in this scenario, the best QP value is selected as 25 and its compressed video is ready to stream. Besides, the NetEM emulator is lunched to simulate the QoS parameters. In this study, the packet loss rate is changed from 0 to 10 to show its impact on the QoE of end-users. Table 5 presents the results of PSNR/SSIM versus packet loss rates for H.265/H.266 standards.

Table 4: PSNR/SSIM vs. QP for low motion streamed video 2K.

QP	H.265	H.266
	SSIM/PSNR	SSIM/PSNR
0	0.993/49.83	1/inf
5	0.982/45.46	0.998/53.87
10	0.956/41.28	0.983/47.49
15	0.916/38.24	0.971/42.18
20	0.888/36.42	0.914/38.15
25	0.87/35.01	0.905/37.34
30	0.841/33.1	0.895/36.55

The NetEM emulator was deployed to replicate Quality of Service (QoS) parameters, specifically targeting the simulation of varying network conditions. In this experiment, the packet loss rate was systematically adjusted from 0% to 10% to evaluate its influence on the Quality of Experience (QoE) perceived by end-users. This assessment is crucial for understanding the degradation effects on video streaming quality, particularly when using advanced video compression standards. Table 5 details the correlation between packet loss rates and the resulting video quality metrics, including Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM), for the H.265 and H.266 video codecs. The data highlights how packet loss rates adversely affect video quality, providing insight into the robustness of these compression standards under varying network conditions. The results underscore the importance of managing packet loss in maintaining high-quality video transmission, particularly in networks utilizing these advanced codecs.

Table 5: PSNR/SSIM vs. packet loss for optimal QP=25.

Packet Loss (%)	H.265	H.266
	SSIM/PSNR	SSIM/PSNR
0	0.9263/34.36	0.9198/33.87
1	0.9193/33.66	0.9102/32.58
2	0.9145/32.92	0.8981/31.66
3	0.9020/31.63	0.8969/31.54
4	0.8896/31.02	0.8875/30.74
5	0.8892/30.85	0.8869/30.63
6	0.8793/30.12	0.8685/28.36
7	0.8681/28.98	0.8709/29.45
8	0.8613/28.78	0.8612/28.79
9	0.8607/28.07	0.8631/28.62
10	0.8479/27.79	0.8411/27.80

Figure 6 presents the PSNR of the low motion streamed video for a wide range of packet loss rates when the QP value 25 is chosen.

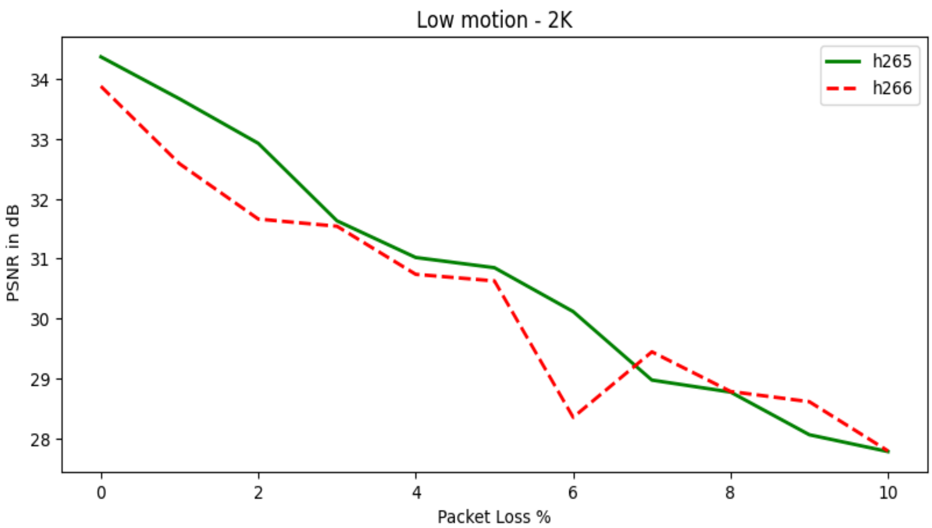


Figure 6: PSNR vs. packet loss for low motion 2K.

4.2. High Motion Video Results

In table 6, the results of PSNR and SSIM for QP values are presented using H.265 and H.266 codecs. When QP value is 30, the PSNR values are close for the codecs with the compressed video size (H.265 – 12.1 MB) and (H.266 – 11.0 MB) respectively. Therefore, in this scenario, the best QP value is selected as 30 and its compressed video is ready to stream. Besides, the NetEM emulator is launched to simulate the QoS parameters. In this study, the packet loss rate was changed from 0 to 10 to show its impact on the QoE of end-users.

Table 6: PSNR/SSIM vs. QP for high motion streamed video 2K.

	H.265	H.266
QP	**SSIM/PSNR**	**SSIM/PSNR**
0	0.995/49.93	1/inf
5	0.988/45.66	0.995/52.64
10	0.973/42.68	0.991/47.38
15	0.951/38.35	0.97/42.55
20	0.922/35.42	0.962/38.64
25	0.881/32.68	0.934/35.64
30	0.823/30.04	0.863/32.56

Table 7 presents the results of PSNR/SSIM versus packet loss rates for H.265/H.266 standards.

Table 7: PSNR/SSIM vs. packet loss for optimal QP=30.

	H.265	H.266
Packet Loss (%)	**SSIM/PSNR**	**SSIM/PSNR**
0	0.8681/30.13	0.8565/27.94
1	0.8470/28.45	0.8397/27.13
2	0.8587/29.09	0.8111/25.25
3	0.8130/25.95	0.7996/25.16
4	0.7953/24.84	0.7920/24.35
5	0.7871/24.68	0.7740/23.68
6	0.7726/23.59	0.7660/23.32
7	0.7719/23.84	0.7526/22.73
8	0.7472/22.74	0.7482/22.75
9	0.7356/22.43	0.7414/22.37
10	0.7236/22.03	0.7398/22.48

In figure 7, we present a comprehensive analysis of PSNR metrics for high-motion streamed videos, all evaluated with a selected QP value of 30. This visualization showcases the system's performance across a spectrum of packet loss rates. The PSNR metric is a crucial indicator of video quality, measuring the fidelity of the received video compared to the original content. By examining PSNR at different packet loss rates, we gain valuable insights into how the system copes with adverse network conditions, providing critical data for optimizing the streaming experience and ensuring superior video quality, even in challenging scenarios.

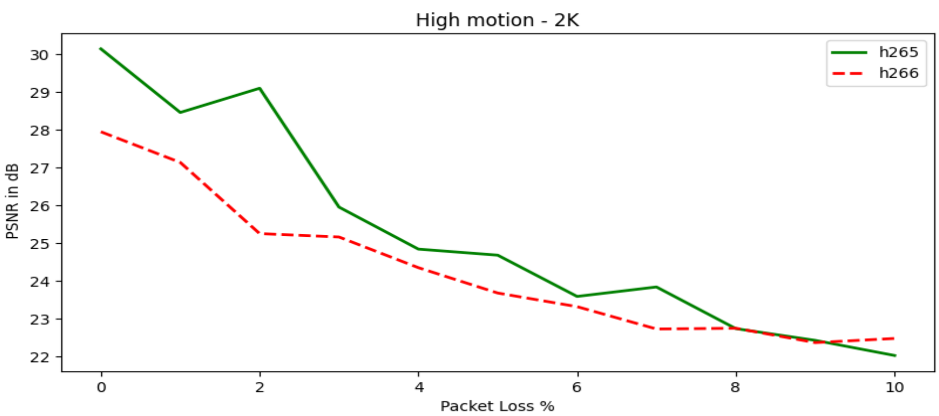


Figure 7: PSNR vs. packet loss for high motion 2K.

Finally, the effect of packet loss on the SSIM values is illustrated in figure 8. Clearly, the degradation in packet loss significantly impacted the QoE perceived by end-users in the case of high-motion video, regardless of whether H.265 or H.266 codecs were employed. While for low motion video, SSIM has higher values and there is a slight change between H.265 and H.266. As a result, both standards can satisfy the end-users during the streaming phase, especially the low packet rate.

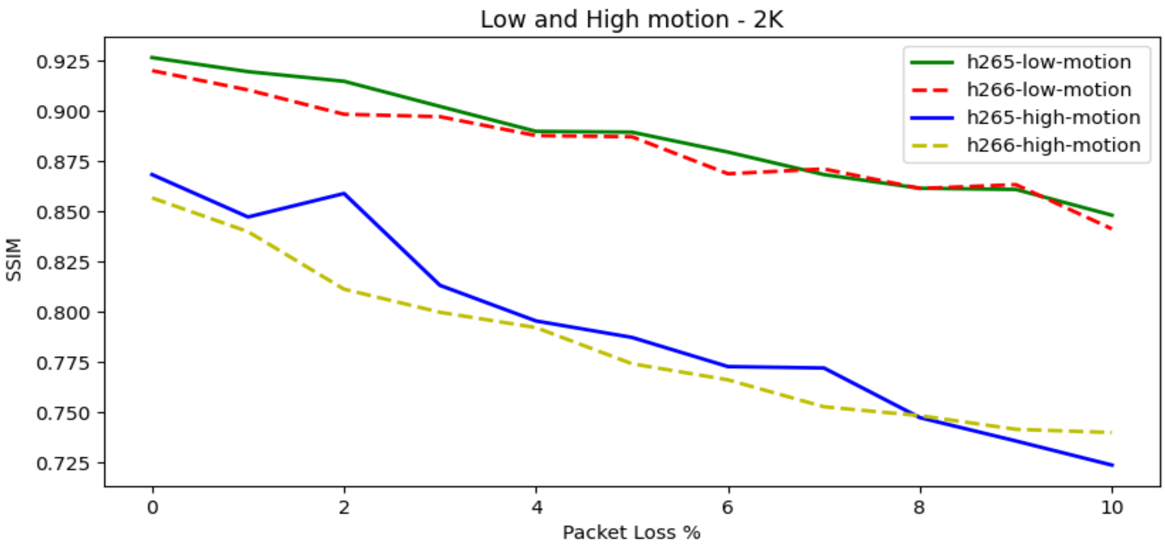
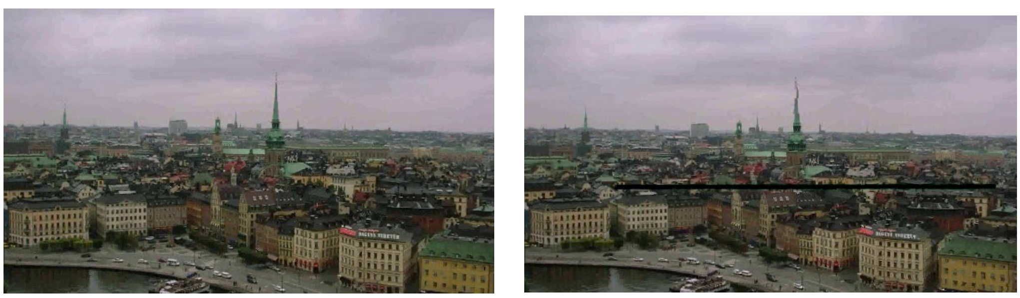


Figure 8: SSIM vs. packet loss for high motion 2K.

4.3. Visual Distortion (Low and High Motion)

Videos can be degraded while streaming between clients and servers due to the variation of QoS parameters such as (packet loss, delay, jitter). In this paper, the effect of network packet loss variation is investigated using H.265/H.266 standards for low and high motion videos. Figure 9, 10, 11 and 12 present the visual distortion effect for 5% and 10% packet loss rates respectively. According to the findings, for both low and high motion, the quality of the streamed video of H.266 has a better result with PSNR = 25.91 dB for the low motion and PSNR = 19.41 dB for the high motion.



(a) Impact of Network Packet Loss (5%) **(b) Impact of Network Packet Loss (10%)**

Figure 9: Visual distortion for Low motion (H.265, QP=25 , PSNR=20.86).

(a) Impact of Network Packet Loss (5%) **(b) Impact of Network Packet Loss (10%)**

Figure 10: Visual distortion for Low motion (H.266, QP=25 , PSNR=25.91).

(a) Impact of Network Packet Loss (5%) **(b) Impact of Network Packet Loss (10%)**

Figure 11: Visual distortion for High motion (H.265, QP=30 , PSNR=18.35).

(a) Impact of Network Packet Loss (5%) **(b) Impact of Network Packet Loss (10%)**

Figure 12: Visual distortion for High motion (H.266, QP=30 , PSNR=19.41).

5. Dicussion

This section provides an in-depth analysis of the proposed system's performance, focusing on its efficiency and effectiveness in video compression, particularly in the context of different video content types and network conditions. The architecture of the proposed system plays a pivotal role in optimizing video streaming performance, especially when processing both low-motion and high-motion sequences. The experimental framework was meticulously crafted to evaluate the system's adaptability and performance across various scenarios, including adjustments in bitrate, frame rate, and network parameters like packet loss. The advanced video compression capabilities of the H.265 and H.266 codecs were central to this investigation, chosen for their potential to enhance video quality while maintaining efficient data compression.

In the low-motion video tests, the system's response to a Quantization Parameter (QP) value of 25 was scrutinized. This parameter was selected to assess the system's ability to preserve video quality while achieving efficient compression. The results indicated that the PSNR values for both H.265 and H.266 codecs were closely matched, with H.265 producing a video file size of 3.5 MB, whereas H.266 achieved a more compressed size of 2.54 MB. This finding underscores the superior compression efficiency of H.266, which is particularly advantageous in environments with bandwidth constraints or limited storage capacity. The minimal difference in PSNR between the two codecs suggests that, for low-motion content, both codecs deliver similar quality levels, though H.266 offers a better balance between quality and compression. For high-motion content, the experiments employed a QP value of 30 to evaluate how the system handles more complex and dynamic video sequences. The PSNR values remained comparable between the codecs, with H.265 generating a video size of 12.1 MB and H.266 producing a slightly smaller size of 11.0 MB. Although H.266 continues to demonstrate better compression, the advantage is less significant in high-motion scenarios compared to low-motion content. The necessity for a higher QP value in high-motion videos reflects the increased complexity of the content and the system's need to balance visual quality with efficient compression. This balance is crucial, as high-motion videos impose greater demands on both the encoder and the network.

The impact of network conditions, particularly packet loss, was thoroughly evaluated using the NetEM emulator. By varying the packet loss rate from 0% to 10%, the study examined the effects on the Quality of Experience (QoE) for end-users. The findings revealed that packet loss has a negative impact on video quality, especially in high-motion content, where the degradation in QoE was more severe. Despite these challenges, H.266 demonstrated a slight edge over H.265 in maintaining video quality under adverse network conditions, indicating that H.266 may offer better resilience to packet loss, particularly in high-motion scenarios.

When this study compared to previous works referenced in [10] and [16], as shown in Table 8, the proposed system, utilizing H.265 and H.266 codecs, shows significant improvements in handling both low and high-motion content at a moderate bitrate of 25 Mbps via RTP. Unlike the method described in Reference [10], which employed H.264/H.265 codecs with a bitrate range of 1-15 Mbps, the proposed system offers superior compression efficiency and quality. Additionally, compared to the system in Reference [16], which utilized H.265/H.266 codecs but required a much higher bitrate of 80 Mbps, the proposed system achieves better performance with lower bandwidth requirements, making it more suitable for real-time applications. The proposed system's PSNR values for both low and high-motion content were superior to those reported in the earlier references, further validating its effectiveness in delivering high-quality video under varying conditions.

Table 8. Comparasion between proposed system, [10] and [16].

Feature	Ref [10]	Ref. [16]	Proposed System
Codec	H.264/H.265	H.265/H.266	H.265/H.266
Motion Type	N/A	N/A	Low and High Motion
Bitrate	1-15 Mbps	80 Mbps	25 Mbps
Protocol	RTP/UDP	N/A	RTP
PSNR (Low Motion)	33.66 dB (H.265) / 32.58 dB (H.266)	Not Provided	Superior to References 10 & 16
PSNR (High Motion)	28.45 dB (H.265) / 27.13 dB (H.266)	Not Provided	Superior to References 10 & 16

6. Conclusions

This paper provides a detailed examination of video streaming performance over wireless networks, focusing on the interplay between video codec types and bitrates. It investigates the impact of varying network packet loss on video quality, utilizing two codec standards—H.265 and H.266—for compressing raw videos stored in MP4 containers. Optimal quantization parameter (QP) values were determined for low (QP=25) and high (QP=30) motion videos. The UDP protocol was employed to stream these compressed videos under different packet loss conditions. Results demonstrated the importance of Quality of Experience (QoE) for both end-users and video streaming services, with PSNR values of 33.66 dB and 32.58 dB for H.265 and H.266, respectively, under 1% packet loss for low-motion videos, and 28.45 dB and 27.13 dB for high-motion videos.

Future work will focus on two main areas: streaming over noisy channels to maintain video quality and evaluating additional Quality of Service (QoS) parameters, such as jitter and delay, using protocols other than UDP.

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Data availability: Data will be available upon reasonable request.

Conflicts of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Cisco report, [Online]. Available: http://bit.ly/2gg1F6B. [Accessed: June 2023].

[2] M. Taha, A. Canovas, J. Lloret, and A. Ali, "A QoE Adaptive Management System for High-Definition Video Streaming over Wireless Networks," *Journal of Telecommunication Systems (Springer)*, vol. 77, no. 1, pp. 63-81, 2021. DOI: 10.1007/s11235-020-00741-2.

[3] Z. Li, S. Drew, J. Liu, *Fundamentals of Multimedia*, 2nd ed., Prentice Hall, 2021.

[4] M. Ashkan, M. Ghasempour, and M. Ghanbari, "A Smart Packet Type Identification Scheme for Selective Discard of Video Packets," *e-Prime-Advances in Electrical Engineering, Electronics and Energy*, vol. 4, no. 1, pp. 100149, Jan. 2023. DOI: 10.1016/j.prime.2023.100149.

[5] O. Khandu, R. Singh, A. Kaur, T. McGill, M. Dixon, K. Wong, and P. Koutsakis, "Artificial Intelligence-Based Video Traffic Policing for Next Generation Networks," *Simulation Modelling Practice and Theory*, vol. 121, pp. 102650, Nov. 2022. DOI: 10.1016/j.simpat.2022.102650.

[6] S. Seyedmohammad, A. Alnajim, X. Zhu, M. Smith, C. Shen, and L. Cimini, "Traffic Characteristics of Virtual Reality over Edge-Enabled Wi-Fi Networks," *arXiv preprint*, arXiv:2011.09035, Nov. 2020. DOI: 10.48550/arXiv.2011.09035.

[7] J. Malebary, W. Ali, and M. Barukab, "Smart Traffic Shaping Based on Distributed Reinforcement Learning for Multimedia Streaming over 5G-VANET Communication Technology," *Mathematics*, vol. 11, no. 3, pp. 700, Feb. 2023. DOI: 10.3390/math11030700.

[8] U. Tadeus, C. Choppe, and J. Klink, "H.264/AVC and H.265/HEVC Codecs in the IP Environment: A Comparison Study of QoE, QoS and UX," *International Conference on Software, Telecommunications and Computer Networks (SoftCOM)*, pp. 1-6, Sept. 2021.

[9] B. Soulef, R. Khemiri, S. Messaoud, O. Ahmed, and F. E. Sayadi, "Deep Learning-Based Video Quality Enhancement for the New Versatile Video Coding," *Neural Computing and Applications*, vol. 34, no. 17, pp. 14135-14149, Nov. 2022. DOI: 10.1007/s00500-022-05840-1.

[10] J. Bienik, M. Uhrina, L. Sevcik, and A. Holesova, "Impact of Packet Loss Rate on Quality of Compressed High Resolution Videos," *Sensors*, vol. 23, no. 5, pp. 2744, Mar. 2023. DOI: 10.3390/s23052744.

[11] C. Stuart and M. Sayıt, "Low Latency Low Loss Media Delivery Utilizing In-Network Packet Wash," *Journal of Network and Systems Management*, vol. 31, no. 1, pp. 1-24, Feb. 2023. DOI: 10.1007/s10922-022-09712-1.

[12] B. Bross, Y.-K. Wang, Y. Ye, S. Liu, J. Chen, G. J. Sullivan, and J.-R. Ohm, "Overview of the Versatile Video Coding (VVC) Standard and its Applications," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 31, no. 10, pp. 3736-3764, Oct. 2021. DOI: 10.1109/TCSVT.2021.3101953.

[13] B. Lehmann, B. Marpe, D. Biatek, T. Raulet, and M. Le Feuvre, "A Complete End-to-End Open Source Toolchain for the Versatile Video Coding (VVC) Standard," *Proceedings of the 29th ACM International Conference on Multimedia*, pp. 3795-3798, Oct. 2021.

[14] V. Marko, J. Sainio, A. Mercat, G. Gautier, J. Vanne, I. Farhat, P. Cabarat, W. Hamidouche, and D. Menard, "Open-Source Toolkit for Live End-to-End 4K VVC Intra Coding," *Proceedings of the 14th Conference on ACM Multimedia Systems*, pp. 312-317, Feb. 2023.

[15] M. Sugawara and K. Masaoka, "UHDTV Image Format for Better Visual Experience," *Proceedings of the IEEE*, vol. 101, no. 10, pp. 8–17, Oct. 2013.

[16] B. Charles, W. Hamidouche, J. Fournier, N. Sidaty, J. Travers, and O. Déforges, "Perceptual Quality Assessment of HEVC and VVC Standards for 8K Video," *IEEE Transactions on Broadcasting*, vol. 68, no. 1, pp. 246-253, Mar. 2021. DOI: 10.1109/TBC.2021.3059348.
[17] Z. Shang, J. P. Ebenezer, Y. Wu, H. Wei, S. Sethuraman, and A. C. Bovik, "Study of the Subjective and Objective Quality of High Motion Live Streaming Videos," *IEEE Transactions on Image Processing*, vol. 31, no. 2, pp. 1027-1041, Feb. 2022. DOI: 10.1109/TIP.2021.3136723.
[18] M. Taha, J. Lloret, A. Ali, and L. Garcia, "Adaptive Video Streaming Testbed Design for Performance Study and Assessment of QoE," *International Journal of Communication Systems*, vol. 31, no. 9, e3551, Sept. 2018. DOI: 10.1002/dac.3551.
[19] M. Taha and A. Ali, "Smart Algorithm in Wireless Networks for Video Streaming Based on Adaptive Quantization," *Concurrency and Computation: Practice and Experience*, vol. 35, no. 9, e7633, Mar. 2023. DOI: 10.1002/cpe.7633.
[20] M. Malekzadeh, "Perceptual Service-Level QoE and Network-Level QoS Control Model for Mobile Video Transmission," *Telecommunication Systems*, vol. 77, pp. 523–541, May 2021. DOI: 10.1007/s11235-021-00777-y.
[21] M. Šilić, M. Sužnjević, L. Skorin-Kapov, N. Skorin-Kapov, and M. I. Lorenzana, "The Impact of Video Encoding Parameters on QoE of Simulated FPV Drone Control," *Multimedia Tools and Applications*, vol. 83, no. 28, pp. 71525–71557, Feb. 2024. DOI: 10.1007/s11042-024-18442-2.
[22] B. Bross, Y.-K. Wang, Y. Ye, S. Liu, J. Chen, G. J. Sullivan, and J.-R. Ohm, "Overview of the Versatile Video Coding (VVC) Standard and its Applications," *IEEE
[23] F. Chiariotti, "A Survey on 360-Degree Video: Coding, Quality of Experience, and Streaming," *Computer Communications*, vol. 177, pp. 133-155, June 2021. DOI: 10.1016/j.comcom.2021.06.029.
[24] B. Zatt, M. Porto, and G. Correa, "A Systematic Literature Review on Video Transcoding Acceleration: Challenges, Solutions, and Trends," *Multimedia Tools and Applications*, vol. 83, pp. 1-30, 2024. DOI: 10.1007/s11042-023-13987-7.
[25] C. J. Huang, H. W. Cheng, Y. H. Lien, and M. E. Jian, "A Survey on Video Streaming for Next-Generation Vehicular Networks," *Electronics*, vol. 13, no. 3, pp. 649, 2024. DOI: 10.3390/electronics13030649.
[26] H. Mareen, P. Lambert, and G. Van Wallendael, "P-Frame Injection for Efficient Packet-Loss Repair in Ultra-Low-Latency Video Streaming," *IEEE International Conference on Visual Communications and Image Processing (VCIP)*, pp. 1-5, Dec. 2023. DOI: 10.1109/VCIP59821.2023.10402720.
[27] P. Topiwala, W. Dai, and K. Bush, "Bandlimited Wireless Video Communications over Lossy Channels," in *Applications of Digital Image Processing XLIV*, vol. 11842, pp. 105-117, Aug. 2021. SPIE.
[28] G. Esakki, A. Panayides, S. Teeparthi, and M. Pattichis, "A Comparative Performance Evaluation of VP9, x265, SVT-AV1, and VVC Codecs Leveraging the VMAF Perceptual Quality Metric," in *Applications of Digital Image Processing XLIII*, vol. 11510, pp. 181-191, Aug. 2020. DOI: 10.1117/12.2567392.
[29] T. Uhl and C. Hoppe, "A New Parameterized Model for Determining Quality of Online Video Service Using Modern H.265/HEVC and VP9 Codecs," *Journal of Telecommunications and Information Technology*, vol. 2020, pp. 13-22, 2020. DOI: 10.26636/jtit.2020.146220.
[30] M. O. Elbasheer, A. Aldegheishem, N. Alrajeh, and J. Lloret, "Video Streaming Adaptive QoS Routing with Resource Reservation (VQoSRR) Model for SDN Networks," *Electronics*, vol. 11, no. 8, p. 1252, 2022. DOI: 10.3390/electronics11081252.
[31] *Multimedia Communication*, [Online]. Available: https://multimediacommunication.blogspot.com/2020/10/happy-world-standards-day-2020.html. [Accessed: July 2023].
[32] J. Klink and T. Uhl, "Video Quality Assessment: Some Remarks on Selected Objective Metrics," in *International Conference on Software, Telecommunications and Computer Networks (SoftCOM)*, Split, Croatia, pp. 1-6, Sept. 2020. DOI: 10.1109/SoftCOM50211.2020.9238248.
[33] M. Behzadpour and M. Ghanbari, "Improving Precision of Objective Image/Video Quality Meters," *Multimedia Tools and Applications*, vol. 82, no. 3, pp. 4465–4478, Mar. 2023. DOI: 10.1007/s11042-022-13416-8.