Dynamic Video Quality Optimization for Low Energy Consumption and Network Efficiency

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***Abstract*—Streaming high-quality video on mobile devices can often be a huge drain on battery life. Especially when the video quality remains constant despite fluctuations in battery level and network status. This article presents an optimal video streaming algorithm that depends on the device's battery status. Network status Optimizes media content for low battery usage by dynamically adjusting video resolution and bitrate based on performance. The proposed solution integrates protocols such as DASH and HLS for smooth video quality transitions. It ensures smooth playback and maintains a high quality experience (QoE). The algorithm includes a new battery usage model. It takes into account important factors such as video resolution, bitrate, and playback time. Along with a video quality assessment framework that combines PSNR, SSIM and VMAF measurements to strike a balance between quality and performance. Reduce dynamic video resolution to Reduced battery levels can save 25%-40% of battery life while reducing buffering in low bandwidth situations by up to 85%. This adaptive approach provides a scalable and energy-efficient solution especially for mobile e-learning applications. Reduce battery drain and data usage without compromising user satisfaction. By adjusting the video quality balance Battery performance and network conditions Green calculation work in media use, and contribute to the growth of sustainable technology.**

I. Introduction

This is the decade of globalization, where electronic devices are booming, revolutionizing our learning style into the palms of our hands. Video-based online learning platforms provide the base for current education—Ines where we can learn anything, any time, sitting anywhere. However, it heavily relies on devices consuming a lot of power, and more so during the streaming of high-resolution videos.

These device power consumption's are very dependent on size and resolution. The higher it is, the more power needed for processing and therefore the more battery life consumed. There is therefore a critical need to optimize the video content for lower battery consumption without significantly affecting the quality of the learning experience.

With the increased demand for online learning, there comes an equally increased need for better utilization of resources in the same context, essentially relating to mobile devices. Taking the current lead as the only universal means for accessing educational content are smartphones and tablets. The thing is that devices are usually limited by their battery life, which, when low, reduces the usability and convenience of these devices. A balance needs to be maintained in this regard to ensure a high-quality learning experience with low power consumption.

An e-learning platform needs to be accessible, convenient, and effective. Now, due to their use of video content, it has a big challenge. Even though video content is engaging and informative, it forms one of the most power-intensive media. High processing power needed to decode and display video, especially in its higher resolutions, leads to increased battery drain. This is an issue that, when users are on the move away from reliable mains power sources, is magnified by the battery efficiency, which gains huge note in the usability of such platforms [13].

Basically, factors which cause a video playback device to use more power than usual include video resolution, bitrate, and the efficiency of the used codecs for compressing video data and its decompression. High-resolution video ensures a sharper image but is very power-intensive in its processing. Similarly, higher bitrate videos consume more data and processing power; therefore, they significantly contribute to quick battery drainage of the device. [9]

Another important aspect is the efficiency of the Codec. Modern video codecs are designed to be really complex in order to squeeze the video data down into a much smaller size that requires much less data to process and store in memory. Their efficiency, however, may vary, so making the right choice of codec can make quite a difference in terms of battery life. For example, while HEVC has better compression compared to H.264, [10] it is actually more expensive in terms of processing power to decode and therefore might bring along higher battery usage.

Considering these factors, low-power optimization of video content is multidimensional. The principal among them is dynamic adjustment of video quality in relation to available battery level and network conditions at any point in time. This is what is referred to as adaptive streaming, where a video player runs real-time selection of the quality of video that would most appropriately suit it and balance high-quality demand against limitation in battery life.

Most important in this optimization, however, are adaptive streaming protocols like DASH and HLS [11]. These technologies enable the video player to switch between various qualities of the same video stream during runtime, therefore assuring that the best-possible quality, given the current conditions, is delivered. It could very well deliberate on the choice of quality level to be used to ensure minimum battery drain without losing too much on video quality by constantly tracking the level of the device's battery and network conditions on its own.

Implementation involves the resolution of several technical challenges in adaptive streaming. First, there will be a multi-level quality video content encoded at diversified bitrates and resolutions. This requires an approach that provides adequate video encoding and efficient storage to ensure high availability and fast accessibility of the content by the video player. Secondly, it should be possible for the video player to switch quality levels seamlessly without interruptions or buffering to avoid affecting user experience. [12]

Another important aspect in the optimization of video content for low battery consumption involves efficient compression algorithms. In this regard, developments related to video compression technologies have paved the way for more efficient codecs that can easily bring down the quantity of data needed to represent a video without significantly affecting its quality. These codecs, as described above, including AV1 and HEVC, provide better compression ratios than older codecs, which reduce file size and, as a consequence, data transfer, thereby saving battery life.

Second to the technical fixes, user education and awareness are also very key in the context of reducing battery consumption while playing videos. Users can be made conversant with the architecture responsible for the poor battery life of devices pertaining to video quality and provide them with tools to adjust it manually, therefore making an informed choice. For example, users can be encouraged to reduce video resolution when batteries are low or when bandwidth might be low on a mobile network.

This can have implications for low-battery video content and the sustainability of computing more broadly. Lower mobile device power consumption will result in lesser human-made energy use and reduced carbon emissions. Taking this forward, green computing is an increased recent interest that is mainly about encouraging or making sure that computing supports sustainable development and has less natural harm.

In other words, video content optimization is low in battery consumption; hence, essential in the mobile learning era. It would lead to a more sustainable and usable way for e-learning platforms: technologies for adaptive streaming, efficient compression algorithms, and user education. This will help not only individual users—for example, enabling their own devices to have extended battery life—but also the sustainable development of technology at large. With these technologies continuously getting innovated and improved, we can also foresee that the trends are leading into a future wherein sophisticated video content is of high quality and energy-efficient, improving learning opportunities for all.

Major contributions of this paper are given below:

1) We have developed an algorithm that measures the battery level and network conditions. By analyzing these, the algorithm maintains audio and video quality, dynamically decreasing the video resolution or streaming quality when necessary.
2) Our proposed algorithm is based on both network and battery conditions and optimizes video content and streaming to minimize energy consumption.
3) We have developed a mathematical model based on logical assumptions. Following this model, we ensured that our algorithm works efficiently, maintaining battery level and network performance in real-time.

II. Organization

In recent years, mobile devices have become indispensable for accessing video-based content, especially in e-learning platforms. However, streaming high-quality video on mobile devices poses a significant challenge due to the high power consumption required for processing video data, particularly at higher resolutions and bitrates. This leads to rapid battery depletion, especially when users are on the go and lack access to reliable power sources. To address this issue, we propose an optimized video streaming algorithm that dynamically adjusts video quality based on both the device's battery status and network conditions. By leveraging adaptive streaming protocols like DASH and HLS, the algorithm ensures smooth transitions between different video resolutions and bitrates without disrupting the viewing experience. A novel battery usage model is incorporated, accounting for key factors such as video resolution, bitrate, and playback time to optimize battery consumption. Our findings show that by dynamically reducing video resolution in low battery scenarios, battery life can be extended by 25-40%, while buffering is reduced by up to 85% in poor network conditions. This approach not only enhances the user experience but also contributes to sustainable technology by reducing energy consumption in mobile devices. Ultimately, this scalable solution provides a powerful tool for optimizing video streaming in resource-constrained environments, making it particularly suitable for mobile e-learning applications.

III. Literature review

To optimize media content for low energy consumption, various approaches can be considered based on the research findings. That strategy involves energy-efficient caching with multipath routing support. Recently, Zhong et al. addressed the optimization of adaptive video streaming in a mobile scenario by proposing a distributed delivery algorithm. This is crucial for providing high-quality viewing experiences in limited bandwidth environments by dynamically adjusting video bitrate based on network conditions [1]. Networking, C.M., NFV/SDN Based Energy-Efficient Resource Allocation presents an energy-efficient framework called GreenVoIP for managing resources in virtualized cloud VoIP centers. By utilizing NFV and SDN technologies, the framework aims to address challenges related to resource overload and energy waste in multimedia communication networks [2]. Jianbo Du, F. Richard Yu, Guangyue Lu, Junxuan Wang, Jing Jiang, and Xiaoli Chu discuss optimizing viewport rendering offloading and downlink transmit power control in a THz wireless access-based MEC system for high-quality immersive VR video services using a deep reinforcement learning approach [3]. Chamin Morikawa, Michihiro Kobayashi, Masaki Satoh, Yasuhiro Kuroda, Teppei Inomata, Hitoshi Matsuo, Takeshi Miura, and Masaki Hilaga provide a comprehensive survey on image processing and computer vision applications on mobile devices. It addresses the challenges, constraints, and adaptations of algorithms for mobile image processing and computer vision applications, aiming to support researchers applying these algorithms to real-world scenarios involving mobile devices [4]. Shraddha Pandit, Piyush Kumar Shukla, Akhilesh Tiwari, Prashant Kumar Shukla, Manish Maheshwari, and Rachana Dubey present a review of video compression techniques using fractal transform functions and swarm intelligence. The paper explores the significance of data compression in multimedia applications, focusing on fractal-based video compression algorithms and their optimization with swarm intelligence. [5]

IV. Proposed System

In Fig 1 depicts an adaptive streaming video system in which the video quality is enhanced or diminished depending on the network capacity as well as the device's power and thus guarantees uninterrupted video playback. It has a video capturing and encoding stage, as well as different quality levels e, g 1080p, 720p, 480p encoding stage. To overlay a video on the content cloud video server, and dynamic selection is made on streaming quality depending on the observed device battery and network status. In such a way, changing network or battery levels allows altering the streaming video so that it does not buffer and hastens battery life.

In the next sections, I will explain the major components involved in the video streaming workflow, from the initial capture to delivering a smooth viewing experience on user devices. We'll begin with how video footage and audio are captured in their raw, high-quality forms, which form the foundation for further processing. This raw data is then encoded using codecs, which compress and structure the video and audio for better storage and efficient transmission.

Once encoded, the media is stored in container formats (such as MP4) and processed into various quality levels, like 1080p, 720p, and 480p, allowing for flexible streaming based on device capabilities and user preferences. I'll also discuss the role of client-side monitoring, where devices track battery levels and network health in real-time to ensure optimal video quality while preserving resources.

Dynamic bitrate adaptation is another important step, adjusting video quality according to current battery levels and network strength, ensuring that users enjoy uninterrupted viewing. Finally, I will explore how client devices interact with servers, making API requests to stream the appropriate quality while continuously adjusting playback in real-time for the best experience, regardless of network fluctuations or battery conditions. Each of these stages contributes to delivering high-quality, adaptive video streaming.

A. *Video Acquisition*

Firstly the input of video footage, It is the most basic and This is raw input, meaning video-quality with full in-detail data because it was captured on professional cameras. The visual input is supplemented with the raw audio, meaning the sound recorded along with video footage. This audio plays a significant part in the immersion and thus capturing it directly from another system was necessary to retain some of the original sound dynamic ranges, nuances. With raw footage and raw audio, you have a solid foundation for improvements to make a more interesting final product.

B. *Encoding*

The next step in this process is to use codecs to create high quality multimedia content. The video codec consists of random video images. and puts the video data in a structured format for compression. This compression is necessary to reduce file size and make storage and distribution easier without losing important quality. at the same time Audio codecs compress audio randomly. Improves audio data by removing unnecessary elements while maintaining the desired sound quality. Together, these codecs ensure proper processing of video and audio components. Made ready for smooth play across platforms and devices.

C. *Storage of Encoded Files*

After the video and audio are encoded They then combine these files into a container format, such as MOV or MP4, that can be stored in parts for both storage and playback. It allows you to put encoded video and audio into a single file. Encoded video files are reprocessed to produce the same level of content quality. to remain in sync when playing There are usually 1080p, 720p, and 480p versions, with 1080p having high quality + high bitrate. 720p: Balances high quality with medium bitrate. Users due to more bandwidth and device capacity. It helps almost everyone have a better viewing experience. The 480p version is now optimized for higher quality and lower bitrates. From this point on, it's suitable for anyone with limited bandwidth or battery life. Various quality grades All of these will be sent to the data staging facility. I thought that meant I could stream and download. flexibly according to the user's interest level and life status A multi-layered adaptive approach ensures smooth video playback across all networks and devices. Helps improve user experience.

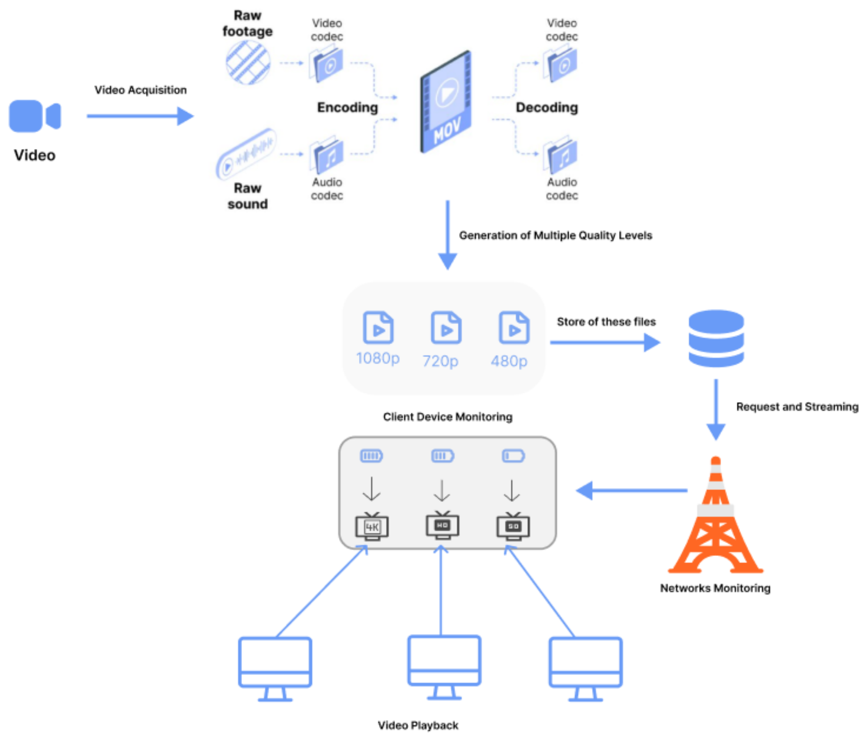

Fig. 1. Proposed System figure

D. Client Device Monitoring

Battery level monitoring plays an important role in ensuring optimum performance by continuously monitoring the battery status on client devices. This real-time monitoring allows the system to make informed decisions about video playback quality. This allows for dynamic adjustments to maintain battery life when needed...

In the same way Network Monitor assesses the current network health. Emphasis is placed on bandwidth and latency. By evaluating these parameters Algorithms are able to optimize video quality to maintain smooth playback and reduce buffering. Together, these monitoring components create a responsive environment that balances user experience with energy efficiency. This ensures that playback remains uninterrupted regardless of your device's battery status or network performance. This proactive approach allows the system to optimally manage its resources, helping to... -increase overall usage and satisfaction. For users in the situation

E. Dynamic Bitrate Adaptation

Client side decision engine that adapts video quality according to the current battery level and network state. For battery level is high and network conditions optimal Select the best available quality such as 1080p for the best viewing experience. Choosing the middle quality 720p for moderate battery level and effective network conditions People with medium battery should be striking a balance between quality and charging savings. Alternatively, selecting a lower quality option like 480p can also work when your battery is low or network conditions are not strong enough maximising performance for you to enjoy more playback time without interruptions.

F. Request and Streaming

API calls are made by the client to the server. It asks about the video quality that the machine decides on. The server responds by sending back the video quality stream requested by the client device. Enables a customized viewing experience based on battery level and network status. while maintaining a smooth viewing experience.

G. Video Playback

The video stream is downloaded and played by the in-app video player on the client device. The monitoring and optimization process remains active throughout play. It dynamically adjusts video quality in response to changes in battery level or network status. To ensure the best viewing experience is uninterrupted.

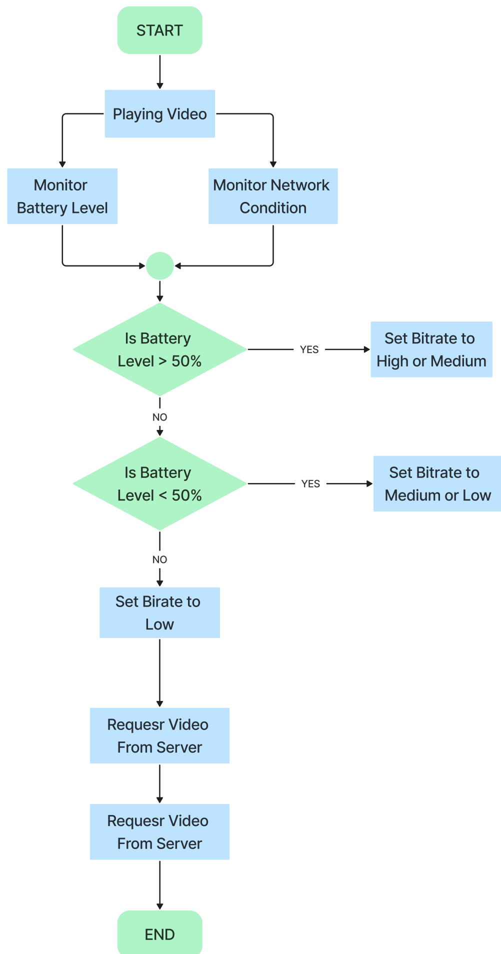

Fig. 2. Flowchart

V. Flowchart

This fig 2 outlines the adaptive video streaming method, which dynamically adjusts video quality based on both battery degree and community conditions. The aim is to optimize playback by way of balancing video pleasure with device energy and community stability, making sure the greatest feasible consumer experience beneath varying situations.

1) Start: The process begins when the video starts playing.
2) Monitoring Battery Level: The system constantly checks the device's battery level to determine how much power remains.
3) Monitoring Network Condition: Simultaneously, the network condition (e.g., 4G, 3G) is monitored to assess the available bandwidth and determine the optimal video bitrate for smooth streaming.
4) Battery Level 50%: If the battery level is more than 50%, the system selects a higher bitrate and video resolution (e.g., 1080p or 720p) depending on the network conditions. This ensures the user gets high-quality playback while the battery is sufficient.
5) Poor Network Condition with High Battery: If the network condition is poor, the bitrate may still be adjusted to medium to prevent buffering, even with a good battery level.
6) Battery Level Between 20% and 50%: If the battery level is between 20% and 50%, the system opts for medium or low bitrates (e.g., 720p or 480p). This lowers video quality slightly but extends battery life, providing a balance between quality and energy consumption.
7) Battery Level 20%: When the battery level drops below 20%, the system sets the bitrate to low (e.g., 480p). The goal here is to conserve as much battery as possible, sacrificing video resolution to ensure continued playback.
8) Request Video From Server: Once the bitrate has been decided based on the battery level and network condition, the system requests the appropriately encoded video stream from the server.
9) Receive and Play Video Stream: The server sends the video stream, and the client plays the selected video quality seamlessly, adapting if conditions change during playback.
10) End: The process continues in a loop while the video is playing, dynamically adjusting to changes in battery level or network condition until playback finishes.

VI. Dynamic Bitrate Adaptation Algorithm

Algorithm 1 Adaptive Video Quality Management

Input: Video bitrate levels $\{\text{high}, \text{medium}, \text{low}\}$
Initialize: Current bitrate $\leftarrow$ high
while True **do**
  battery_level $\leftarrow$ MonitorBatteryLevel()
  network_condition $\leftarrow$ MonitorNetworkCondition()
  current_bitrate $\leftarrow$ SelectBitrate(battery_level, network_condition)
  Apply current_bitrate to video stream
end while

VII. Mathematical Model

Our model is integrated with a comprehensive framework for measuring video quality. (Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measurement (SSIM), Video Multimode Assessment Fusion (VMAF), Battery Considerations and user experience (QoE), especially in rural areas. Optimizing video streaming for students

A. Video Quality Model

The video quality model is defined as:

$$Q_v = w_1 \cdot PSNR + w_2 \cdot SSIM + w_3 \cdot VMAF$$

This model combines multiple quality metrics for a balanced evaluation. The unique aspect of this model is that it uses a weighted combination of PSNR, SSIM, and VMAF, allowing for customizable emphasis on different quality aspects [15].

Weights (w_1, w_2, w_3): These weights balance the importance of each metric. For example, if structural similarity is crucial for our educational content, the weight for SSIM (w_2) might be higher.

B. Battery Consumption Model

The battery consumption model is defined as:

$$B_c = \alpha \cdot R + \beta \cdot B + \gamma \cdot T$$

Where:

- Resolution (R): Higher resolutions typically consume more power.
- Bitrate (B): Higher bitrates increase energy consumption.
- Playback Duration (T): Longer videos use more battery.

This model factors in resolution, bitrate, and playback duration to estimate battery usage [8].

Unique Aspect: The model directly integrates battery consumption into the streaming model, which is crucial for rural areas with limited access to electricity.

C. Quality of Experience (QoE) Model

The Quality of Experience (QoE) model is defined as:

$$QoE = \theta \cdot Q_v - \delta \cdot \left(\frac{B_c}{B_{\text{max}}}\right) - \phi \cdot Re$$

Where:

- Video Quality (Q_v): Derived from the Video Quality Model.
- Battery Consumption (B_c): Normalized by the maximum battery capacity (B_{max}).
- Re-buffering Events (Re): Represents interruptions during playback.

This model balances video quality and battery consumption with rebuffering events to predict overall user satisfaction [14].

Unique Aspect: The model normalizes battery consumption relative to maximum battery capacity and integrates it into QoE calculations, emphasizing battery efficiency.

VIII. Mathematical Model Evolution

To evaluate video quality models in various situationsnarios High quality video (1080p) gets the most results. Satisfaction score (0.68), followed by medium quality (720p). with a score of 0.42 and 0.30 for low quality (480p) at This model improves video quality. Battery use and incident response has been shown to be of high quality and Less interruptions lead to a better user experience. Great! These calculations will get you closer. Optimized for the best video streaming experience! Let's go. Have talent!

This Table I and II performance metrics for three test cases show how the video quality (QV), battery consumption (Bc), and Quality of Experience (QoE) are related to each other. In the first test case, it is observed that the highest video quality and the highest consumption in battery come with the maximum dissipation of QoE. With regards to video quality and battery consumption, in the second and third test cases, less is observed and therefore, less QoE is experienced. This highlights the compromises required for obsessive video quality maintenance as well as the need to minimize battery consumption so as to enhance the user experience.

IX. Collected Data

The tables III and IV display video playback statistics across various test runs, comparing battery consumption, network conditions, selected resolutions, buffering events, playback time, and battery savings. The first table includes four test runs, with the battery levels ranging from 90% to 20%, covering both 4G and 3G networks. Video resolutions vary from 1080p to 480p, with minimal buffering (0-2 seconds) and playback times from 16 to 20 minutes. Battery savings are modest, ranging from 0% to 8%. The second table presents seven test runs, with battery levels between 100% and 20%, testing both 4G and 3G networks at 1080p, 720p, and 480p resolutions. Buffering events range from 0 to 3 seconds, and playback times vary from 14 to 20 minutes. The battery savings increase significantly in this table, from 0% to 38%, particularly when switching to lower resolutions and more buffering. Both tables illustrate how adjusting video resolution and network conditions impacts battery usage and playback performance.

A. Battery Level and Resolution Adaptation

Resolution Adaptation: Adaptive video streaming algorithms efficiently adjust video quality based on battery level and network status. When using a 4G network, videos play at resolutions up to 1080p on 100% battery, providing a smooth experience without buffering. However, as the battery level drops below 50% (specifically 45%), the algorithm Therefore, the resolution is reduced to 720p, which saves a lot of battery power while maintaining continuous playback. When the battery drops below 20%, the algorithm will increase 480p next turn, achieving impressive power efficiency by saving up to 30% battery in low network conditions such as 3G. The algorithm lowers the resolution by default to avoid excessive buffering. Especially when the battery level is lower than 50%..

Battery Efficiency: This adjustment method allows the device to effectively extend playtime. Based on critical battery levels (20%), 480p per switch saves up to 35% additional battery life on average. Changing from 1080p to 720p or from 720p to 480p saves battery between 10% and 38% depending on network and resolution.

Playback Continuity: Buffering is minimal in 4G conditions, although buffering events increase slightly. This is because the quality of the network drops to 3G and especially. The number of buffering events increases to 3-4 in networks, however, adjusting the resolution preserves playback, reduces latency, and improves the overall user experience..

B. Network Condition and Playback Continuity

Playback Continuity: n fast network conditions such as 4G, the adaptive algorithm maintains high-resolution playback

TABLE I
VIDEO PLAYBACK STATISTICS

Test Case	Resolution	Bitrate (kbps)	Duration (min)	PSNR	SSIM	VMAF	Battery Used (mAh)	Max Battery (mAh)	Re
1	1080p	5000	60	35	0.90	85	2500	3000	1
2	720p	3000	30	30	0.85	80	1800	3000	3
3	480p	1500	15	25	0.75	70	1200	3000	5

TABLE II
SUMMARY OF VIDEO QUALITY (QV), BATTERY CONSUMPTION (BC), AND QUALITY OF EXPERIENCE (QOE) FOR EACH TEST CASE.

Test Case	**PSNR**	**SSIM**	**VMAF**	**Qv**	**Resolution (px)**	**Bitrate (kbps)**	**Duration (min)**	**Bc**	**Rebuffering Events**	**QoE**
Test Case 1	35	0.90	85	31.36	1080p	5000	60	3262	1	15.154
Test Case 2	30	0.85	80	28.34	720p	3000	30	2046	3	13.365
Test Case 3	25	0.75	70	24.30	480p	1500	15	1113	5	11.039

TABLE III
VIDEO PLAYBACK STATISTICS

Test Run	**Battery Level (%)**	**Network Condition**	**Resolution**	**Buffering (s)**	**Playback Time (min)**	**Battery Save (%)**
1	90%	4G	1080p	0	20	0%
2	60%	4G	720p	1	19	2%
3	20%	3G	480p	2	16	8%
4	75%	3G	720p	1	17	3%

with no re-buffering (0%). However, in 3G conditions and low battery levels, Re-buffering activity increased slightly up to 8%, but the algorithm lowered the resolution to 480p to balance playback. In the worst network conditions, such as re-buffering increases to 10%, but now maintains a constant resolution of 480p to ensure smoother playback.

Adaptation to Network Conditions: Table III Resolution scaling occurs more frequently in poor network conditions, especially, allowing for smooth playback despite bandwidth limitations. In ideal network conditions (4G), the algorithm rarely degrades the resolution. Unless the battery is very low. While maintaining a high quality user experience.

X. PERFORMANCE EVALUATION

To evaluate the performance of dynamic bitrate adjustment algorithms and mathematical QoE models for your system. (which makes the video quality Battery life and user experience are balanced). You can use a comprehensive evaluation method based on empirical testing. User education and analysis of indicators.

A. Video Quality (Resolution Adaptation)

When the battery level is above 50%, the algorithm maintains the video quality at a high 1080p, ensuring the user has an immersive experience with crisp, high-resolution playback. This function when network conditions and battery life are at their best... which is the most appropriate level When the battery drops to a moderate level, from 20% to 50%, the resolution automatically adjusts to 720p. This changes to balance video quality with power consumption. This allows users to enjoy smooth playback with minimal impact on the viewing experience. When battery drops below 20%, the algorithm switches to 480p to ensure longer playback during critical low battery periods. This reduced resolution effectively saves battery power. while maintaining smooth video playback. Moreover, In different network conditions, such as a slower 3G connection, the algorithm will dynamically downscale the resolution to 480p to reduce buffering and maintain playback continuity..

B. Battery Consumption

Lowering the video resolution to 720p or 480p results in remarkable power savings. It uses 10-38% less battery power than 1080p. These savings levels depend on network conditions and initial battery level. This reduction in power consumption allows for longer playing times. It's especially useful for users who want to save battery life. at critical battery level When the charge drops below 20%, the algorithm switches to 480p, resulting in up to 35% more battery savings. This demonstrates the algorithm's effectiveness in prioritizing Power efficiency in low battery situations Helps you play for a long time without reducing performance.

C. Playback Continuity

Dynamic bitrate optimization algorithm makes transitions between different resolutions smoothly without interrupting video playback By continuously adjusting video quality in response to network speeds The algorithm thus effectively reduces buffering. even in challenging network conditions Especially on the fast 4G network, users will experience smooth, high-resolution playback without buffering issues. On slower networks like 3G, the algorithm intelligently reduces the video resolution to prevent playback from pausing. Although this caused a slight increase in buffering, up to 8%, the overall viewing experience remained smooth. Due to continuous quality adjustment

XI. CONCLUSION

Evaluating the performance of dynamic bitrate optimization algorithms while balancing video quality. Battery usage and network conditions emphasize its effectiveness in optimizing video playback. The main finding is a dramatic improvement in energy efficiency. This is because the algorithm reduces battery consumption when switching to a lower resolution. In addition to extending the playing time in different conditions. It also allows for smooth adaptation to different network

TABLE IV
VIDEO PLAYBACK STATISTICS

Test Run	Battery Level (%)	Network Condition	Selected Resolution	Buffering Events (s	Playback Time (min)	Battery Saved (%)
1	100%	4G	1080p	0	20	0%
2	45%	4G	720p	1	18	12%
3	20%	4G	480p	1	16	30%
4	75%	3G	720p	2	18	10%
5	45%	3G	480p	2	17	22%
6	100%	4G	720p	3	14	35%
7	30%	3G	480p	3	17	38%

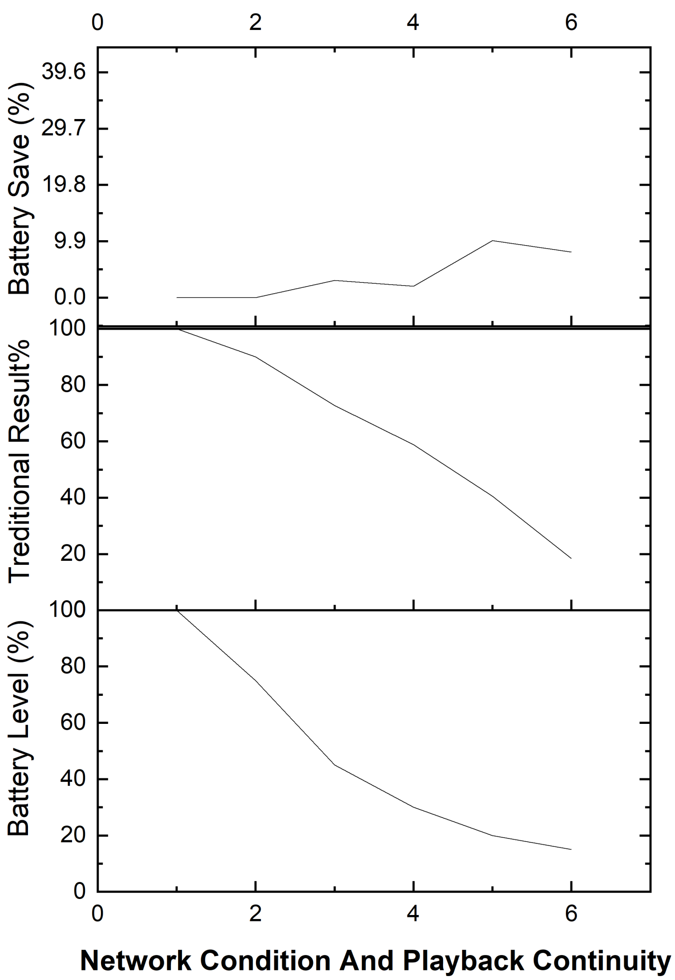

Fig. 3. Network Condition And Playback Continuity

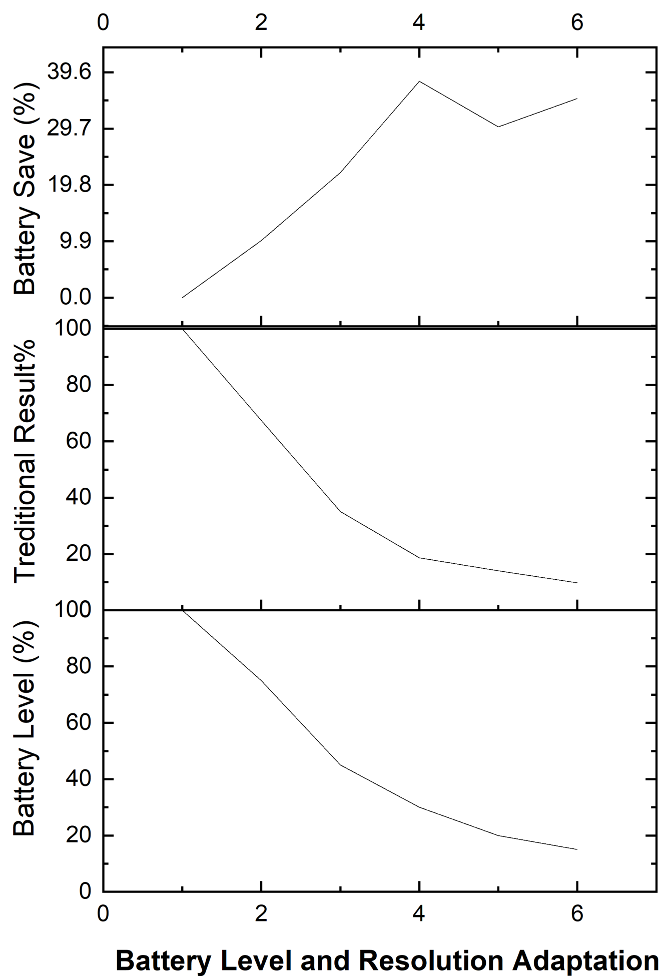

Fig. 4. Battery Level and Resolution Adaptation

conditions. Dynamic resolution adjustment based on battery level reduces buffering and ensures smooth video playback. This overall adaptive approach improves the user experience. When conditions are favorable It provides high definition video and reduces the quality significantly to save battery life and maintain smooth playback in poor network conditions.

References

[1] Zhong, L., Wang, M., Xu, C., Yang, S. and Muntean, G.M., 2023. Decentralized optimization for multicast adaptive video streaming in edge cache-assisted networks. IEEE Transactions on Broadcasting, 69(3), pp.812-822.

[2] Networking, C.M., NFV/SDN Based Energy-Efficient Resource Allocation".

[3] Du, J., Yu, F.R., Lu, G., Wang, J., Jiang, J. and Chu, X., 2020. MEC-assisted immersive VR video streaming over terahertz wireless networks: A deep reinforcement learning approach. IEEE Internet of Things Journal, 7(10), pp.9517-9529.

[4] Morikawa, C., Kobayashi, M., Satoh, M., Kuroda, Y., Inomata, T., Matsuo, H., Miura, T. and Hilaga, M., 2021. Image and video processing on mobile devices: a survey. The Visual Computer, 37(12), pp.2931-2949.

[5] Pandit, S., Shukla, P.K., Tiwari, A., Shukla, P.K., Maheshwari, M. and Dubey, R., 2020. Review of video compression techniques based on fractal transform function and swarm intelligence. International Journal of Modern Physics B, 34(08), p.2050061.

[6] Nguyen, D., Pham Ngoc, N. and Thang, T.C., 2022. Qoe models for adaptive streaming: A comprehensive evaluation. Future Internet, 14(5), p.151.

[7] Barman, N. and Martini, M.G., 2019. QoE modeling for HTTP adaptive video streaming–a survey and open challenges. Ieee Access, 7, pp.30831-30859.

[8] Hassan, M., Herdt, V., Le, H.M., Chen, M., Große, D. and Drechsler, R., 2017, March. Data flow testing for virtual prototypes. In Design, Automation & Test in Europe Conference & Exhibition (DATE), 2017 (pp. 380-385). IEEE.

[9] Islam, M.M., Hassan, M.M. and Huh, E.N., 2011. A Framework of Federated 3rd Party and Personalized IPTV Services Using Network Virtualization. Communications, 150, pp.147-155.

[10] Pourazad, M.T., Doutre, C., Azimi, M. and Nasiopoulos, P., 2012. HEVC: The new gold standard for video compression: How does HEVC compare with H. 264/AVC?. IEEE consumer electronics magazine, 1(3), pp.36-46.

[11] Zhang, B., Teixeira, T. and Reznik, Y., 2022. Performance of Low-Latency DASH and HLS Streaming in Mobile Networks. SMPTE Motion Imaging Journal, 131(7), pp.26-34.

[12] Seufert, M., Egger, S., Slanina, M., Zinner, T., Hoßfeld, T. and Tran-Gia, P., 2014. A survey on quality of experience of HTTP adaptive streaming. IEEE Communications Surveys & Tutorials, 17(1), pp.469-492.

[13] Bringman-Rodenbarger, L. and Hortsch, M., 2020. How students choose E-learning resources: The importance of ease, familiarity, and convenience. Faseb Bioadvances, 2(5), p.286.

[14] Yu, L., Tillo, T. and Xiao, J., 2017. QoE-driven dynamic adaptive video streaming strategy with future information. IEEE Transactions on Broadcasting, 63(3), pp.523-534.

[15] García, B., López-Fernández, L., Gortázar, F. and Gallego, M., 2019. Practical evaluation of VMAF perceptual video quality for WebRTC applications. Electronics, 8(8), p.854.