Modeling Video Playback Power Consumption on Mobile Devices

Bekir Turkkan
IBM Research
Yorktown Heights, NY, USA

Adithya Raman
University at Buffalo
Buffalo, NY, USA

Tevfik Kosar
University at Buffalo
Buffalo, NY, USA

Abstract

Advancements in mobile hardware and streaming technologies enable high-quality video streaming for mobile users, but this comes at a cost: a boost in power consumption. Despite detailed studies on power consumption during acquisition, existing studies fall short of considering recent technologies and, hence, of accurately capturing video playback power consumption. This paper presents a novel method to model mobile video playback power consumption. First, we identify the major components contributing to power consumption during video playback on mobile devices. Then, we develop models for each component to estimate their power consumption. Our experimental results show that our combined model estimates power consumption with 91% mean accuracy. Furthermore, our model maintains its high accuracy on an unseen device, achieving 88% mean accuracy despite the hardware and screen heterogeneity.

CCS Concepts: **• Information systems → Multimedia streaming**; **• Hardware** → *Platform power issues.*

Keywords: Video streaming, energy, mobile devices

ACM Reference Format:
Bekir Turkkan, Adithya Raman, and Tevfik Kosar. 2024. Modeling Video Playback Power Consumption on Mobile Devices. In *Second International ACM Green Multimedia Systems Workshop (GMSys '24), April 15–18, 2024, Bari, Italy.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3652104.3652837

1 Introduction

Mobile video streaming represents 71% of global mobile traffic as of 2023 and is expected to exceed 80% by 2028[6]. The widespread adoption of Dynamic Adaptive Streaming over HTTP (DASH) [1] technology has enabled the surge in video streaming traffic. DASH provides multiple versions of videos and lets clients select a suitable version for each video chunk. Advancements in mobile device and networking technologies, along with DASH, enable clients to stream high-quality videos. However, it can cause a significant decrease in battery life, up to 50% faster compared to browsing [7, 11] and 75% faster than audio streaming [12]. Factors such as screen brightness, video quality, network conditions, and video codec determine the power consumed. Thus, modeling power consumption requires analyzing these components.

Prior modeling studies have employed different approaches. Chen et al. [13] present a model that uses the encoding bitrate and the network signal strength. Herglotz et al. [16] analyze video streaming components separately and propose a feature selection model. Similarly, Yue et al. [20] proposes component-based models for regular and 360° videos. All the above models work on devices with liquid crystal display (LCD) screens and omit light-emitting diode (LED) screens despite significant differences in their patterns. These approaches and their limitations are further explained in Section 2.

This paper makes the following contributions: (1) We analyze the impact of each factor of mobile adaptive video playback with a series of controlled experiments. (2) We develop separate models for both LED and LCDs as well as video processing, allowing us to account for differences in power consumption patterns between these types of displays. (3) We evaluate the accuracy of our combined video playback power consumption model, which considers both display and processing power. Our results show that the model estimates the power consumption with up to 91% accuracy for the training device and achieves an average accuracy of 88% on an unseen device.

2 Background and Related Work

Modeling the power consumption of video streaming is vital for sustainability. Existing studies suggest different approaches. Chen et al. [13] present a quadratic function using encoding bitrate and signal strength to estimate power consumption due to downloading and playing videos simultaneously. For local playback intervals, they use a linear function of encoding bitrate. Herglotz et al. [16] consider data acquisition, video processing, display, audio processing, and speaker as the significant components of video streaming power consumption. They analyze each component theoretically

GMSys '24, April 15–18, 2024, Bari, Italy

ACM ISBN 979-8-4007-0617-2/24/04…$15.00
https://doi.org/10.1145/3652104.3652837

and propose a combined model for total power consumption. They find throughput, display brightness level (for LCD screens), and video frame rate are significant parameters that enable accurate modeling.

Yue et al. [20] propose different models for CPU, display, network, and residual power components. For the CPU component, they use CPU frequency and utilization and baseline power consumption for all active cores. They suggest constant power consumption due to display for a given brightness level. For the network component, they only consider the network throughput while using different coefficients for WiFi and LTE connections. Finally, they calculate residual power consumption by subtracting CPU, network, and display components from total power consumption. GreenABR [19] presents a model to capture the power consumption pattern of ABR streaming components. It uses the power model to guide the ABR agent and does not target estimating power consumption.

All of the above studies suggest that the network throughput level decides the data acquisition power consumption. Similarly, the component-wise models find frame rate as a significant parameter. However, they either do not model display power consumption or consider only LCD screens, which have significantly different behavior than LED screens. We further examine their differences with our experiments in Section 3.3. Similarly, they all present custom coefficients for each device rather than having a more general model, which requires having the same set of measurements for each new device and calculating the corresponding coefficients.

Addressing the aforementioned limitations of existing models motivates our work. Specifically, we identify all major parameters of video processing and display components and propose a combined model to estimate video playback power consumption for different screen types (i.e., LCD and LED) and unseen devices.

3 Components of Mobile Video Playback Power Consumption

This section analyzes the video processing and display components regarding video playback power consumption. We present the results of our controlled experiments for the impact of encoding parameters, genre, and display components.

Experimental Setup: In our experiments and evaluations, we used Samsung XCover Pro (XCover) and Samsung Galaxy S21 (S21) phones with Android 11.0. We collected power measurements for both phones with the Android battery manager (ABM) [15]. We also used Monsoon power monitor [3] for XCover to confirm ABM measurements since it has a removable battery. The "Big Buck Bunny"[4] video encoded with AVC codec is used for all video experiments and training of our models. We played our videos with ExoPlayer [2] and displayed our images with a modified Glide Slider[8] application. In all of our experiments, we used representations

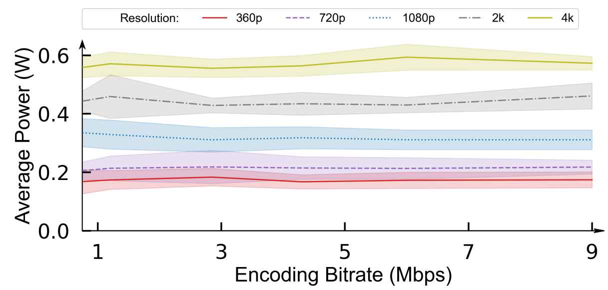


Figure 1. Impact of encoding bitrate and resolution on XCover.

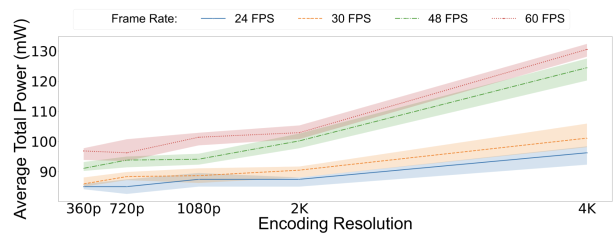


Figure 2. Impact of frame rate and resolution on S21.

supported by our phones. Therefore, we did not observe any software decoder activity. We ran our experiments five times and used average results for each analysis and evaluation.

3.1 Impact of Encoding Parameters

Encoding Bitrate and Resolution. Video encoding solutions commonly target using an equal amount of data per second based on a given bitrate [5]. Similarly, resolution decides the number of pixels processed for each frame during encoding and playback. In this experiment, we encode videos for different bitrate levels from 0.7 to 9 Mbps for the same resolution and codec and repeated the experiment for five different resolution levels. Figure 1 shows that power consumption is nearly constant for XCover despite increasing encoding bitrate as found in [10]. The shaded area represents the standard deviation during five repetitions of experiments, which is comparable for different bitrates. On the other hand, resolution mainly decides the power consumption, as increasing resolution increases power consumption significantly. The results for S21 are quite parallel, with a relatively higher standard deviation due to screen technology differences. We should note that existing works [13, 16] consider bitrate as a major component since they use a single bitrate for each resolution.

Frame Rate. Frame rate determines the number of frames used for each second of a video. Video content creators use high frame rates to store more details for content with high motion rates, such as sports videos. Similar to resolution, it decides the number of pixels to be processed and impacts

Table 1. Comparison of power consumption of videos in different genres.

Video	Genre	360p (mW)	720p (mW)	1080p (mW)	Phone
TOS	Sci-Fi	2103	2160	2254	XCover
Sintel	Animation	2089	2164	2252	XCover
BBB	Cartoon	2105	2201	2282	XCover
Samsung	Sports	2134	2190	2271	XCover

the power consumption. In this experiment, we encoded our video with four commonly used frame rates and five different resolutions. Figure 2 shows that increasing the frame rate significantly impacts power consumption for any video resolution on S21. It is the largest for 4K videos, as expected, due to the boost in total pixels to be processed on the hardware decoder. Despite the differences in the amount, XCover has a similar power consumption pattern.

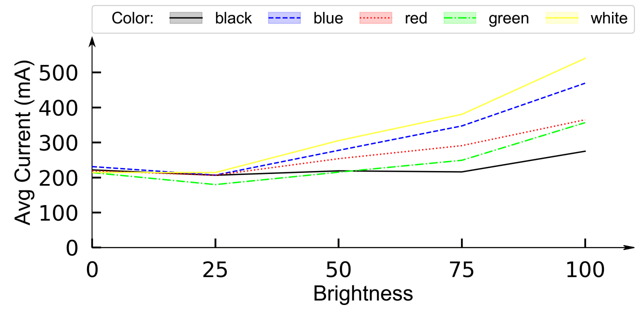
Video Codec. In this experiment, we encoded videos with AVC and VP9 codecs and analyzed the difference in power consumption due to the codec. We found a matching power consumption pattern for both codecs, while VP9 consumes slightly more power than the AVC codec. However, we should also note that VP9 is known to achieve the same quality with lower data usage.

3.2 Impact of Video Genre

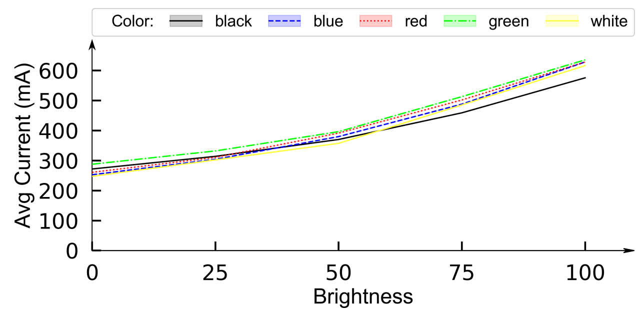
Videos may have different characteristics, such as motion rate and shot proximity. To understand their impacts on power consumption, we conducted experiments on four videos, "Big Buck Bunny" (BBB), "Tears of Steel" (TOS), "Sintel", "Samsung Sports Video" (Sports), from cartoon, animation, sci-fi, and sports genres. In general Cartoon videos have the lowest spatiotemporal image complexity while it is much higher for Sci-Fi and Sports videos where the motion is more unpredictable. We encoded videos for the same representation sets in our experiments and compared their average power consumption. Table 1 shows that video content has a minor impact on power consumption on XCover. We observed slightly more differences for S21 due to the color rate of images as explained in Section 3.3.

3.3 Impact of Display Parameters

Lighting technology is the dominant factor in display power consumption. LCD screens use constant light resources for brightness, while LED screens change the light amount based on the color levels in RGB channels. In this regard, we tested S21 (LED) and XCover (LCD) with black, blue, red, green, and white images. We displayed single-color images for five brightness levels, 0, 25, 50, 75, and 100%, and collected power consumption measurements.



(a) LED screens (S21)



(b) LCD screens (XCover)

Figure 3. Impact of brightness and color on power consumption.

Brightness. Screen brightness level affects the power consumption for both LCD and LED displays. Higher brightness levels require more power consumption for both, although the relations between their slider brightness level and power consumption differ. In LCD screens, the brightness level decides the voltage on the backlight source and has almost a linear relationship with the corresponding power consumption[17]. On the other hand, Phones with LED screens convert the slider brightness from 0-100 scale to 0-255 scale to find the system brightness level. This corresponds to a nearly logarithmic relationship between them[14]. Figure 3 shows that brightness is linearly related to the power consumption of LCD screens, while it differs based on the colors of the pixels for LED screens.

Color. The color rate of pixels impacts only LED displays' power consumption since each pixel is lighted separately. For instance, they do not use any light source for a pixel with an entirely black color while they use whole light for a white color pixel. Figure 3a indicates that the power consumption difference is minimal for shallow brightness levels. At the same time, it becomes significant for a 100% brightness level, which aligns with the findings in a current study on the power consumption of applications with different color schemes[14]. It also shows that power consumption change is almost negligible for black images despite the increasing brightness. Shutting off the corresponding LED lights for black pixels causes this behavior. The color rate may have a minor impact on LCD screens that use TFT layers with LED light sources as shown in Figure 3b.

Our experiments suggest that resolution, frame rate, screen brightness, and screen type are the most significant parameters. In addition, we found the screen to be the primary source of device heterogeneity and the most dominant power consumption component. In the next section, we design a new model to estimate video playback power consumption using the significant parameters above.

4 Design

The power consumption of video streaming has five essential components: *video processing*, *displaying video files*, *data acquisition*, *audio processing*, and *speaker operations* [16]. We model the consumption of the first two components as the most relevant to video playback power consumption. The data acquisition power consumption is the same as downloading files over HTTP and mainly depends on network throughput and technology as discovered in existing studies [16, 18, 20, 21]. Audio files are commonly provided in a single version, encoded with a high bitrate due to their negligible file sizes compared to video files. In addition, speaker power consumption is highly affected by user preferences. Therefore, we excluded these components from our modeling work to focus only on video playback elements.

4.1 Display Power Consumption Model

Mobile device displays use two standard display technologies, LCD and LED, which cause heterogeneous power consumption patterns. Existing studies [16, 20] commonly model LCD displays and suggest constant power consumption for a given brightness level. However, the color rate of displayed frames significantly impacts the power draw for LED screens, especially for high brightness levels. In this section, we first confirm the linear relation between brightness level and LCD energy consumption and then present a model for LED screens that uses brightness level and color rates to estimate instantaneous current usage. Instantaneous power consumption, $P = V * I$, where I is the current level and V is the voltage, can easily be calculated using the current level since device batteries supply a constant voltage level.

Power consumption of LCD displays. In our experiments on LCD displays, we found a linear relation between brightness level and power consumption. We also discovered a significant base power consumption due to the active light source even for zero brightness level. In this regard, we design a linear function, Equation 1 where $\mathtt{I_d}$ is the current level due to display, $\mathtt{I_{base}}$ is the idle current to operate the device, $\mathtt{I_{ls}}$ is the base current to feed the light source, and *Br* is the brightness level.

$$\mathtt{I_d} := \mathtt{I_{base}} + \mathtt{I_{ls}} + \alpha * \mathsf{Br} \tag{1}$$

Power consumption of LED displays. Our experiments indicate that brightness level and color rate must be considered for modeling LED display power consumption. The impact of brightness level is extensively different for frames with different color rates. For instance, increasing the brightness levels does not impact black pixels, while it is dominant for white pixels. Similarly, the color does not change the power consumption for shallow brightness levels, while it has a significant impact when brightness levels approach 100%.

Dataset: We collected power measurements on S21 while displaying 125 generated single-color images using five values for RGB channels. We repeated our experiments for 0,25,50,75,100% brightness levels five times. Due to the difference in the brightness and RGB channel data scales, we normalized our data with the maximum value for each variable. We split our dataset as 80% for training and 20% for testing randomly.

First, we consider that each color channel impacts the power consumption independently, and the brightness level affects the overall power consumption with their combined contribution. Thus, we use a straightforward linear function in Equation 2, where I_t is the estimated current at time t, br_t is the brightness level, r_t, g_t, and b_t are the RGB channel values of the frame respectively. α parameter corresponds to the base current level to operate the device while $\beta, \gamma, and \mu$ are the coefficients for individual impacts of color channels.

$$\mathtt{I_t} := \alpha + br_t * (\beta * r_t + \gamma * g_t + \mu * b_t), \tag{2}$$

Next, to analyze the compound impact of brightness level and color channels, we train a linear regression model with a neural network (NN) of one input layer, two hidden layers, and a single output layer. We use the root mean squared error (RMSE) for our loss function as shown in Equation 3, where p_t is the predicted current, and o_t is the observed instant current value at the time t. Our inputs include the values of RGB channels and the brightness level, while the output only has the estimated current level.

$$\mathsf{RMSE} := \sqrt{(p_t - o_t)^2}, \tag{3}$$

We train a Scikit-learn KerasRegressor model through a pipeline that evaluates the model with ten-fold cross-validation and 250 epochs. Our model achieves an RMSE of 0.0041 as a cross-validation score with a 0.0004 standard deviation on the test set.

4.2 Video Processing Power Model

Measuring video processing power consumption on mobile devices is not trivial. We observed that when the device screen is locked, the video player application stops processing the frames even though it continues buffering them. To this end, we collected instant current levels by streaming BBB video for 20 representations: 360p, 720p, 1080p, 1440p, and 2160p resolutions, and 24, 30, 48, and 60 frame rates. To obtain the current values due to processing, first, we calculated the average color levels of each second of the video and

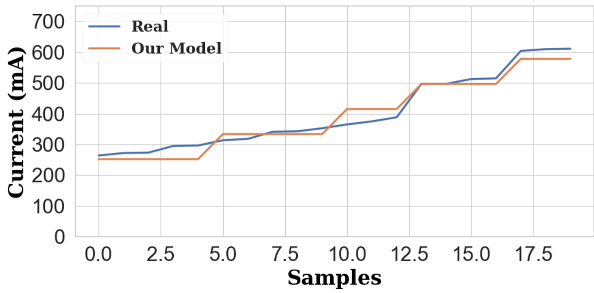


Figure 4. LCD power consumption model evaluation.

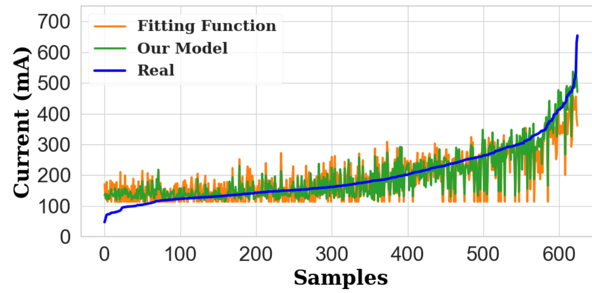
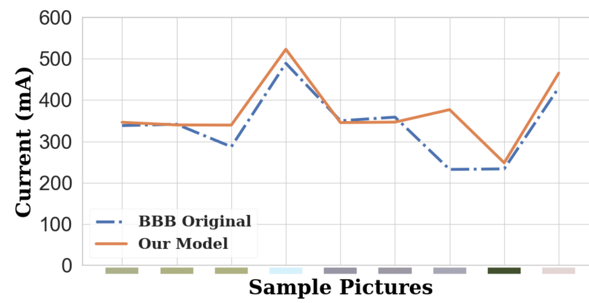
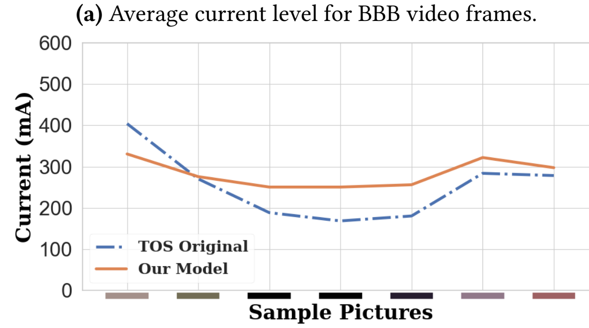


Figure 5. LED power consumption models evaluation.



(a) Average current level for BBB video frames.



(b) Average current level for Tears of Steel video frames.

Figure 6. Comparison of estimated and actual current levels of individual frames. The average colors are shown for each frame as x-axis labels.

used our display power model to estimate the corresponding current usage. Then, we subtract the screen's current usage from the total video playback current usage. Our experiments encountered that resolution and frame rate are the major components of processing power consumption.

Training. We train another regression model using the same neural network structure and training process as the display power model. We feed the input layer with the normalized data for video height, width, and frame rate. We use the same loss function, RMSE, in Equation 3. Our model achieves a 0.0065 cross-validation score with a 0.0023 standard deviation on the test set.

5 Evaluation

This section explains our evaluations for display and video processing power models. We evaluate the display models independently. Then, we explain our results for the combined video playback power consumption model. We used S21 and XCover for our experiments. We used only the S21 dataset to train the video processing model and evaluated it with both phones.

5.1 Display Power Consumption Model

LCD Display Power Consumption. We optimize our linear function in Equation 1 for the training set of our measurement data and find the parameters as $\mathtt{I}_{1s} = 0.273$ and $\alpha = 0.527$. Figure 4 indicates that our calculation method accurately estimates the current level with around 6% estimation error on XCover.

LED Display Power Consumption. We evaluated both linear function and NN-based regression models over the test set on S21. For the linear model in Equation 2, we optimized our function for the training set and found the parameters: $\alpha = 0.174$, $\beta = 0.111$, $\gamma = 0.133$, and $\mu = 0.239$. Figure 5 shows that our NN-based regression model achieves an RMSE of 0.0047 compared to the linear fitting function with an RMSE of 0.0076.

To evaluate our display power consumption model for regular videos, we selected random frames with different scene characteristics from *BBB* and *TOS* videos. We used our slider application and collected the instant current values for each frame for 30 seconds with S21. We considered a frame would consume a similar amount of power with a new frame created for the average color rate of the selected frame. Thus, we calculated the average color rates of the frames with OpenCV [9] and used them for our model predictions.

Figure 6 shows that our model captures the pattern accurately. BBB frames commonly have brighter colors than TOS frames, and their corresponding current usage is also higher. Our model estimates the instant current with ≈10% error for BBB and ≈12% error for TOS frames. During our experiments, we measured the instant current level at each second and used the average for evaluation. We should note that the standard deviation of these consecutive readings is

Table 2. Video Playback Estimation Accuracy Percentage of S21 and XCover (XC)

		360p		720p		1080p		1440p		2160p	
Video	**FPS**	**S21**	**XC**	**S21**	**XC**	**S21**	**XC**	**S21**	**XC**	**S21**	**XC**
BBB	24	93.8	85.7	91.9	89.3	92.0	93.1	88.7	94.6	83.5	90.2
BBB	30	93.0	89.9	93.5	92.0	93.1	92.5	88.7	93.7	87.9	86.5
BBB	48	93.3	90.7	92.5	92.4	94.2	94.6	89.8	91.6	89.3	77.2
BBB	60	94.1	91.9	94.4	93.8	93.2	91.3	84.4	88.5	89.6	73.6
Sports	24	85.4	87.0	86.0	88.5	88.8	90.5	90.0	92.3	84.1	88.2
Sports	30	89.4	85.0	87.1	91.0	87.6	90.2	86.7	91.0	86.7	87.2
Sports	48	88.8	87.7	87.6	90.6	88.6	89.7	86.5	91.4	86.5	79.5
Sports	60	87.0	89.4	89.1	91.5	84.0	91.5	90.7	92.5	89.7	77.9
Docu.	24	93.5	91.6	86.5	89.6	87.2	91.0	85.9	89.9	89.3	88.23
Docu.	30	91.2	90.8	80.1	91.9	83.0	92.3	86.6	88.6	88.7	85.4
Docu.	48	88.2	90.4	87.3	90.9	84.6	90.6	88.0	91.7	87.8	75.0
Docu.	60	87.4	92.1	90.0	93.3	86.3	90.3	88.5	88.9	91.6	72.5

around 14.5% on average. Our model achieves a lower error rate than the average standard deviation of the actual measurements.

5.2 Local Playback Power Consumption Model

We evaluated our processing power model and display power model together since their integrated performance is what matters for video playback power consumption. For our evaluations, we used sample videos from Highsense in sports and documentary categories in addition to our training video, BBB. We created 20 distortions for each video with five different resolutions and four frame rate levels we used for training data collection. In these experiments, we set the brightness level to 100% since the display power varies more for high brightness levels. We measured the instant current level by playing each video representation separately to avoid any buffering interventions. We calculated the color rates for our videos to feed our display energy model for LED screens, and we used Equation 4 to find the estimated current usage of video playback where I_p is the estimated current level due to video playback, I_d is the estimated current level due to display, and I_{proc} is the current level due to processing.

$$I_p = I_d + I_{proc}, \tag{4}$$

Table 2 shows our estimation accuracy percentage for video playback power consumption for S21 and XCover. Our model performs best with 91% accuracy for BBB on S21 and 90% accuracy with XCover, as expected, since it was used for the training of the processing power model. It achieves 87.5% accuracy on average for both Sports and Documentary videos for S21, while it achieves 88% accuracy for XCover. Considering the standard deviation in actual measurements with around 14.5%, our results indicate that our model successfully generalizes to unseen videos. Similarly, our results indicate that our model generalizes to XCover, which was not used in the training of the processing power model. Since it has an LCD screen, we used the LCD power model for the display component and used the same processing model. Similar processing power consumption patterns and training our model with normalized data led to the compatible performance of our model for the unseen device, XCover. In our results, we observe that the performance of our model degrades for 4K videos for 48 and 60 fps levels. It is due to the hardware decoding limits of the XCover for AVC codec. It simply boosts the energy consumption when it exceeds the capacity, as also found in another existing work [19].

6 Conclusion and Future Work

Video streaming applications significantly drain the batteries of smartphones compared to audio playback or web browsing due to high power consumption during video playback. To model video playback power consumption, we propose separate models for display and processing, with different approaches for LCD and LED displays due to their distinct behavior. Our combined model estimates video playback power consumption with 91% average accuracy, despite the average standard deviation in measurement sensitivity of 14.5%. We also evaluate our model's performance on a different device, achieving less than 3% average degradation.

In the future, we plan to improve the generalization of our models by using transfer learning and tuning coefficients with a few experiments on new devices. Similarly, we will extend our work to tablets with similar technologies.

Acknowledgements

This project is sponsored by the National Science Foundation (NSF) under award number OAC-2313061.

References

[1] 2020. DASH Industry Forum. https://dashif.org/
[2] 2020. Google ExoPlayer. https://github.com/google/ExoPlayer
[3] 2020. Monsoon High Voltage Power Monitor. Retrieved August 19, 2020 from https://www.msoon.com/online-store/High-Voltage-Power-Monitor-Part-Number-AAA10F-p90002590
[4] 2021. Test Media. Retrieved August 19, 2021 from https://media.xiph.org/
[5] 2023. Encoding For Streaming Sites. https://trac.ffmpeg.org/wiki/EncodingForStreamingSites
[6] 2023. Ericsson Mobility Report, 2023. https://www.ericsson.com/49dd9d/assets/local/reports-papers/mobility-report/documents/2023/ericsson-mobility-report-june-2023.pdf
[7] 2023. iPhone 13 series battery life revealed. https://www.phonearena.com/news/apple-iphone-13-series-battery-capacities-leaked_id132514
[8] 2024. Glide Slider. https://github.com/firdausmaulan/GlideSlider
[9] 2024. OpenCV. https://docs.opencv.org/4.x/index.html
[10] Samira Afzal, Narges Mehran, Zoha Azimi Ourimi, Farzad Tashtarian, Hadi Amirpour, R.-C. Prodan, and Christian Timmerer. 2024. A Survey on Energy Consumption and Environmental Impact of Video Streaming. *ArXiv* abs/2401.09854 (2024). https://api.semanticscholar.org/CorpusID:267035135
[11] A. Anastasov. 2023. *Galaxy S22 battery life & tests: upgrade or disappointment?*
[12] Apple. 2023. *Power and Battery.*
[13] X. Chen, T. Tan, and G. Cao. 2019. Energy-Aware and Context-Aware Video Streaming on Smartphones. In *2019 IEEE 39th International Conference on Distributed Computing Systems (ICDCS).* 861–870.
[14] P. Dash and C. Hu. 2021. How Much Battery Does Dark Mode Save? An Accurate OLED Display Power Profiler for Modern Smartphones. In *Proceedings of the 19th Annual International Conference*

on Mobile Systems, Applications, and Services (MobiSys '21). Association for Computing Machinery, New York, NY, USA, 323–335. https://doi.org/10.1145/3458864.3467682

[15] Android Documentation. 2023. *Battery Manager*.

[16] C. Herglotz, S. Coulombe, C. Vazquez, A. Vakili, A. Kaup, and J. Grenier. 2020. Power Modeling for Video Streaming Applications on Mobile Devices. *IEEE Access* 8 (2020), 70234–70244.

[17] M. Schuchhardt, S. Jha, R. Ayoub, M. Kishinevsky, and G. Memik. 2015. Optimizing Mobile Display Brightness by Leveraging Human Visual Perception. In *Proceedings of the 2015 International Conference on Compilers, Architecture and Synthesis for Embedded Systems* (Amsterdam, The Netherlands) *(CASES '15)*. IEEE Press, 11–20.

[18] L. Sun, R. Sheshadri, W. Zheng, and D. Koutsonikolas. 2014. Modeling WiFi Active Power/Energy Consumption in Smartphones. In *2014 IEEE 34th International Conference on Distributed Computing Systems*. 41–51. https://doi.org/10.1109/ICDCS.2014.13

[19] B. Turkkan, T. Dai, A. Raman, T. Kosar, C. Chen, M. Bulut, J. Zola, and D. Sow. 2022. GreenABR: Energy-Aware Adaptive Bitrate Streaming with Deep Reinforcement Learning. In *Proceedings of the 13th ACM Multimedia Systems Conference* (Athlone, Ireland) *(MMSys '22)*. Association for Computing Machinery, New York, NY, USA, 150–163. https://doi.org/10.1145/3524273.3528188

[20] C. Yue, S. Sen, B. Wang, Y. Qin, and F. Qian. 2020. Energy Considerations for ABR Video Streaming to Smartphones: Measurements, Models and Insights. https://dl.acm.org/doi/10.1145/3339825.3391867

[21] L. Zou, A. Javed, and G. Muntean. 2017. Smart mobile device power consumption measurement for video streaming in wireless environments: WiFi vs. LTE. In *2017 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB)*. 1–6. https://doi.org/10.1109/BMSB.2017.7986151