HELP, I SHRUNK MY SAVINGS! ASSESSING THE CARBON REDUCTION POTENTIAL FOR VIDEO STREAMING FROM SHORT-TERM CODING CHANGES

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ABSTRACT

With the effects of climate change globally manifesting, all sectors of the economy and society are aiming to reduce their carbon emissions. Increasing attention is given to the carbon footprint of video streaming. Innovation and optimisation of video codecs can affect the energy consumption in all system parts. Previous work has identified opportunities to reduce electricity consumption, yet methods to reliably estimate the carbon reduction potential from interventions on video streaming systems are currently lacking. In particular, not enough consideration is given to the complex interactions between changes to a service and operational and structural effects at internet-scale systems, and that manifest at varying time scales. This introduces uncertainty. In this text, we review the state of knowledge and propose a marginal approach for the assessment of short-term decarbonisation potential of interventions. We illustrate this with a simplified example intervention, in which we evaluate the temporary reduction of the video resolution of user-generated content video on demand from 1080p to 720p in a fixed ladder scenario over one month in the UK. We find that the carbon reductions mainly come from savings at user devices, but are overall negligible at 0.5gCO2e per day per typical laptop-viewer.

***Index Terms*—** video streaming, video codecs, carbon emissions, sustainability, change-oriented LCA

1. INTRODUCTION

The electricity consumption and associated carbon footprint of video streaming has received increasing attention from the research community [1], organisations providing these services [2], the general public [3], and the regulator [4]. Electricity is consumed by all digital devices that constitute the service system and carbon emissions arise, among others, during the generation of this electricity from fossil fuels. Video is a central element of most online media services, and the processing of video content has been a significant economic driver for the evolution and growth of the Internet and associated devices in datacentres and networks; and with users. Understanding the decarbonisation potential of changes to video technologies (here also referred to as "interventions") is important to purposefully direct the future development of the sector towards greater sustainability. In this text we are evaluating changes to video encoding and the effects on compression. The principles of this inquiry are transferable to other interventions that effect the energy consumption of system parts end-to-end.

The co-evolution of video technology and the Internet and its resulting carbon footprint are complicated and currently insufficiently understood in detail. For example, increasing efficiency over successive generations of video codecs enabled streaming at higher quality, which alongside increasing demand by users, compensated potential reductions in data volume and energy consumption. Even at shorter time scales (i.e. less than months), the energy and carbon effects from optimisations are challenging to assess. For example, a choice between modern codecs requires balancing energy consumption in servers during (de-)compression with savings in data volume affecting storage and network energy consumption. So far, it is unclear how to assess the decarbonisation potential for Internet media services from optimising video codecs. Such an assessment requires a calibrated end-to-end model of the underlying service system that includes the variables affected by codec choices. Building such a model requires not only an understanding of the signal processing part of encoding videos but also of the environmental assessment principles to determine consequent electricity and carbon footprints from servers, networks and user devices at internet scale.

Assessing interventions by comparing two alternatives contrast to attributing part of the current impact to one specific service. Firstly, the effect of background processes that are independent of the intervention to be evaluated, should be accounted for. For example, in the case of video streaming at least two major background, medium-to-long-term processes need to be considered: i) efficiency improvements in hardware (e.g. Moore's law) and software (optimisation), and ii) ongoing changes in average and peak data volumes on networks change the utilisation, efficiency and deployment of devices. And secondly, the structural effects of the intervention need to be assessed (for example resulting behaviour change). This is challenging, and existing assessments of video services treat this inconsistently, not at least because estimating the change of the efficiency of Internet infrastructure is a topic of ongoing debate [5]. Yet, robust and meaningful assessment of the potential of interventions, rather than the system as a whole, are urgently needed as media companies are planning to reduce their carbon emissions.

In this text we aim to progress the development of change-oriented assessments. Our approach is to reduce the complexity of the effects by limiting the duration of the intervention. During the short term, changes to an ICT service (e.g. a change to a video codec) manifest as operational change to power consumption that in turn affects the use-phase energy footprints (i.e. environmental impact from electricity consumption). Beyond the short term, the dynamics of structural changes (e.g. user behaviour adapting to change, background efficient improvements, etc.) will invalidate the steady-state assumptions. In Life Cycle Assessment (LCA) methods, cut-off rules permit the reduction of system boundaries by excluding demonstrably immaterial contributions (as long as there are only a small number of these) [6]. In our case, we limit the temporal system boundary by reducing the time frame of the assessment. While cut-off thresholds are not universal, typical values applied in LCA are in the order of 1 to 5% affect on environmental flow relevant for the functional unit. Considering that the energy intensity of networks so far has reduced around 20 to 30 percent per year [7], a duration of up to three months would remain below a 5% change of efficiency.

In this text we present an environmental assessment model built on LCA principles to evaluate the short-term carbon impact of reducing the volume of data and computation of a video streaming service. Specifically, we analyse a use-case of computing the electricity and carbon savings from streaming User-Generated Content (UGC) through a video streaming platform, such as YouTube, at a lower resolution. For this use case, we assume streaming of High Efficiency Video Coding (HEVC)/H.265 [8] encoded videos at reduced resolution, from Full High Definition (FHD) to High Definition (HD). The scale considered is the average UK consumption of YouTube on smart devices (not including TVs) from statistics derived from Barb [9]. For this analysis, we have collected a new empirical dataset of the video decoding and display power consumption of a subset of the YouTube-UGC dataset [10] on laptop PCs. To the best of our knowledge, this is the first time, an end-to-end modelling and evaluation of UGC video streaming at different resolutions consistent with change-based LCA methods has been attempted.

This text is structured as follows. In Section 2, we review relevant previous studies of the energy and carbon emissions related to video media. Following this, in Section 3, we present a short-term model to assess the carbon effects of changing the resolution of a video stream service. We evaluate the model and show the result in Section 4. We close with a discussion and identify directions for future work in Section 5.

2. BACKGROUND

Attributional LCA Studies of Video Services. Existing end-to-end assessments are either attributional or not consistently following change-oriented methods. Among the first to study the carbon emissions of streaming television were Chandaria et al. [11], who estimated the carbon footprint of streaming BBC iPlayer video to TVs in the UK of 86 gCO2e/viewer-hour in 2009. Schien et al. [12] updated this to 93gCO2e/viewer-hour for the year 2016. Both works provided a comparison of IP-based streaming with broadcast but do not evaluate the impact of changing the video coding technology. Shehabi et al. [13] compared the carbon emissions of US video consumption between streaming and physical DVD shipping and find that streaming is substantially less carbon intense. During their sensitivity analysis they found the Network Energy Intensity (NEI) to be a key assumption.

Research estimating the value of NEI for service assessments with end-to-end scope dates back at least to 2008 [14]. Baliga et al. provided an early analysis of the energy efficiency of networks that included assumptions on real-world utilisation [15]. Recently, Aslan et al. [7] reviewed estimates of the NEI and found that it decreases at a rate of about 30% per year. Aslan et al. provided an estimate of Average NEI (ANEI) and an estimate of an annual improvement rate of ca. 30% p.a. Recently, the discourse has begun to consider how changes of data-use have a marginal affect on the network as a dynamic system. Malmodin [16] aimed to better represent the poor energy proportionality (20%) of wired networks and proposed a new model of the short-term energy intensity that includes a static offset component and a short-run marginal component. The static component is considered fixed and does not account for a change of the allocated base power consumption over time. This model can thus be considered a short-term Marginal NEI (MNEI).

Average, Short and Long-Term Emission Factors. Assessments of carbon emissions of Internet services apply emissions factors to estimates of electricity consumption. Recent work has found that most short-run Marginal Emission factors (MEF) outperform Average Emission factor (AEF) [17]. These short-term MEF, however, do not represent the "influence on the structural evolution of the grid" that electricity consumption has [18]. Gagnon et al. [18] demonstrated the benefits of a long-run marginal model to represent this influence.

Evaluating Energy and Carbon Effects from Interventions on Video. So far, only a small number of works evaluated the carbon potential of interventions on video services. Preist et al. [19] presented a model of the world-wide carbon footprint of YouTube and estimated the carbon savings from eliminating the video bitstream, but keeping the audio data, for a portion of the YouTube videos that are music videos. Assuming the energy consumption by user devices to remain constant and applying ANEI and AEF, they found that such a change could result in significant reduction of energy and carbon emissions in wireless networks between 117 and 586 KtCO2e per year.

The CarbonTrust applied ANEI models in a carbon assessment of video streaming based on models developed by DIMPACT [20] and Netflix [2]. Using an updated value for the ANEI metric by Aslan they estimated the typical carbon footprint per hour streaming for a typical mix of user devices and electricity carbon intensity in the EU to be 55 gCO2e/viewer-hour in 2021. Ignoring effects on user devices and servers, they also compared the effect of bitrate changes, using Malmodin's MNEI and found a negligible effect on wired networks and a substantial effect on wireless networks.

A greater number of works investigated the effects on system parts in isolation, meaning either only the decoding and/or encoding or transmission process [21, 1, 22, 23, 24]. Among them, Ejembi et al. [21] analysed the difference in client device power consumption between Netflix quality settings in 2015 and found an average difference of 3.7 Watts between the lowest and highest levels. A growing number of works modeled the energy consumption of video encoding and decoding. For example, Ramasumbu et al. [1] presented a model to estimate the energy consumption of x265 based on the encoder processing time and proposed a linear model calibrated on the *ultrafast* preset. Herglotz et al. [22] developed a detailed power consumption model for device decoding and calibrated this on a mobile device. Kraenzler et al. [23] further built on this model to explore optimisation strategies of video encoders to improve its energy consumption. Finally, Katsenou et al. [24] conducted a comparative study of the energy-quality-rate tradeoffs of state-of-the-art video codecs on simulations run on a server without however considering the energy consumed by the display.

3. END-TO-END ASSESSMENT OF SHORT TERM EFFECTS

Here we present an assessment of relevant environmentally impact to demonstrate the evaluation of a short-term effect. We reference LCA terminology but do not go into the full detail of a complete LCA assessment. The goal of our LCA is to evaluate the short-term impact of changing the resolution of video streaming of user-generated from 1080p to 720p for laptop PCs. We assume a quality-driven fixed bitrate ladder scenario of streaming at relatively low bitrates following the Google recommendation for VoD [25]. As this recommendation was created for VP9 codec, we match the VMAF quality levels of VP9 encodes at two target bitrates (1024kbps for 720p and 1800kbps for 1080p at 25fps), with H.265 encodes in order to evaluate a comparable quality of service. Thus, we expect a varying range of bitrates around these targets depending on the video content. The video codec implementation used is the optimised software version of H.265 from ffmpeg, libx265 [26], at the medium preset. As for the time and regional scope, we chose 1.3.2020 to 31.3.2020 for the

UK audience of "Social Video on Demand" [27].

Generic End-to-End Model. A generic model of a streaming service system can be seen in Fig. 1. It is similar to those used in previous assessments of social and Subscription/Broadcaster VoD services [19, 2].

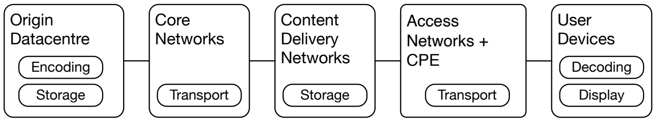

Fig. 1. Simplified generic model of a video streaming service architecture.

The full life cycle of the devices included in the architecture includes the impact from raw material extraction, manufacturing, transport, the use phase, and the end of life phase. Given that we are only considering the short-term impact of the intervention, we assume that the effect is entirely operational and not structural. Specifically, this implies that: i) consumers do not change their behaviour (e.g. change the viewing device, and do not purchase different devices as the consequence of this change), ii) the media provider(s) do not change their encoding strategy (plausible, because this change is limited to a specific region), and thus the required storage space on origin servers does not change.

As we are comparing the impact before and after the change, all LCA phases, except for the use phase, factor out from the assessment. The use phase impact is the sum of the electricity footprint for the five components of the streaming architecture.

Origin Datacentre. The electricity consumption of the origin datacentre that scales with demand for video streaming can be modelled as the sum of the component business functions: encoding $E^{ODC}_{encoding}$, storage $E^{ODC}_{storage}$, serving E^{ODC}_{Tx}, and additional functionality E^{ODC}_{meta} (e.g. analytics and recommendation).

$$E^{ODC} = E^{ODC}_{encoding} + E^{ODC}_{storage} + E^{ODC}_{Tx} + E^{ODC}_{meta} \tag{1}$$

The energy consumption for transmission can be defined as $E^{ODC}_{Tx} = v_{OC} \cdot I^{ODC}_{Tx}$, with v_{OC} the data volume of content that is sent from the origin datacentre to the global network of CDNs, and I^{ODC}_{Tx} the transmission energy intensity of origin servers. We assume that analytics and recommendation workloads are relatively independent on bitrate. In our short-term analysis, encoding and thus storage also remain identical.

Content Delivery Network. Similarly, CDN electricity consumption, E^{CDN}, is the sum of receiving videos from the origin datacentre, storage, and serving.

$$E^{CDN} = E^{CDN}_{Rx} + E^{CDN}_{storage} + E^{CDN}_{Tx} \tag{2}$$

Transmission energy is proportional to data volume and energy intensity: $E^{CDN}_{Tx} = v_{UC} \cdot I^{CDN}_{Tx}$. We assume transmission and receiving energy intensity to be similar. The origin traffic is the hitrate-proportion ($\hat{h}$) of user traffic that misses the CDN cache: $v_{OC} = \hat{h} \cdot v_{UC}$.

Networks. We consider core and access networks (here subsuming customer premise equipment - CPE). Malmodin [16] provides a marginal model for the short-term change of electricity consumption by the network.

$$E_{net} = P^{net}_{sub} \cdot t + v \cdot I_{net} \tag{3}$$

As we are only considering a short-term intervention, the baseload power per subscriber remains constant and thus factors

Variable	Value	Reference
I_{Tx}	13.5 J/Gb	[28] We estimate marginal energy intensity, by assuming 40% base power and PUE of 1.5. We apply the least energy efficient appliance.
I_{Core}	0.03 J/Mb	[16]
I_{Acc}	0.02 J/Mb	[16]
cachemiss rate	0.3	[29]
daily audience	50.7m	[9] Viewing time remained similar since pandemic [27]
viewing time	42 min	Social VoD [27]
bitrate	1.688 Mbps	Own measurements
P_{dec}	6.6 W	Own measurements

Table 1. Main model parameter values. The full dataset and EAM [5] model can be found at [30]

out in our comparison. From the model remain, v the data volume transferred, and I_{net} the dynamic energy intensity of data transfer. While the structure of the model is identical for the core and access network component, the parameter values for the intensity does vary between core and access network (see Table 1).

User Devices For an evaluation of short-term system changes, the energy consumption of the user device can be modelled as the sum of the energy required for receiving and playing (decoding and displaying).

$$E^{UD} = E^{UD}_{Rx} + E^{UD}_{playing} \tag{4}$$

Carbon Emissions. While MEF are most appropriate to estimate carbon emissions in short-term contexts there are many ways to estimate short-run marginal intensities [17]. MEFs change quickly in response to changes in renewable generation and demand and are inherently stochastic at the margins. In the UK this uncertainty is particularly high in the middle of the day. Fine grained Location-based MEF have the potential to reduce this uncertainty. For our current post-hoc evaluation at population-level behaviour over 30 days, this is not an option. And so, for this analysis we evaluate the intervention with a Simplified Thermal MEF (STMEF) (assumed constant from Combined Cycle Gas, ≈394gCO2e/kWh). For the UK, at national level, gas is an adequate proxy for the marginal impact [31]. This STMEF is about 100% higher than the UK AEF.

Bitrate Reduction. As our intervention, we are evaluating limiting the maximum bitrates delivered to viewers for a video streaming service in a fixed ladder use case. This means that specific spatial resolutions can be streamed at different ladder rungs (bitrates). To this end, we have collected new primary data for the decoding and display energy consumption under varying bitrates, as explained in Section 3. Specifically, we measured the average energy consumption for decoding and display on a laptop (Dell XPS 15 bn95209sb; i7-12700H CPU; 32GB Memory, Nvidia 3050 Ti GPU; UHD screen, Fedora 37 Linux) for the YouTube UGC dataset [10] with a R&S HMC8015 power analyzer.

We first computed the VMAF scores of the VP9 version of each source video when encoded at the YouTube target bitrates, and then encoded this with H.265 (libx265) at a QP value to match the delivered quality of service. We selected H.265 video codec, as it is one of the state-of-the-art codecs in terms of compression efficiency used currently for streaming. The selected configuration of the experiment serves the purpose of proof of concept. The experimentation will be further extended in future work.

4. RESULTS

Given our model and the video codec configurations explained in Section 3 we measure a reduction of power consumption on our reference laptop, and estimate the end-to-end carbon footprint reduction from a bitrate change in Figs. 2 and 3, respectively. As anticipated, Fig. 2 shows that in our fixed ladder scenario where different resolutions are streamed at different bandwidths, the power required for decoding 720p is lower than what is required for 1080p. On average the difference of power consumed when decoding on a single laptop is small ($\sim$ 2W).

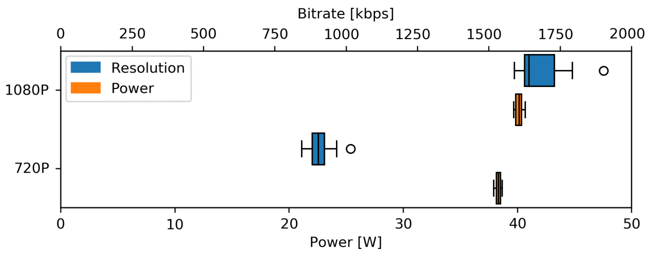

Fig. 2. Comparison of the bitrates of H.265 videos from the YouTube UGC dataset and power draw by a laptop PC during decoding and displaying. Videos are encoded to match the VMAF scores of VP9 encodes at the YouTube target bitrates for 720p and 1080p.

Across the the end-to-end system, the avoided emissions, applying a simplified thermal MEF for viewing on laptops in the month of March 2020 are (all kgCO2e): 287 (Origin Datacentre), 1,248 (CDN), 1,593 (Core Networks), 1,019 (Access Networks), and 119,137 (User Devices). This equates to 0.5gCO2e saved per person per day. Figure 3 shows how these reductions vary over the course of the day. In order to illustrate the effect of the choice of MEF, we compare the savings with a statistical MEF [32] based on historical generation and carbon emissions data and taking the regression slope of the change in carbon intensity against change in generation (delta-kgCO2e/delta-kWh) from the UK National Grid [33] for each half hour of generation, over March 2020; labeled monthly average MEF (MAMEF). The MAMEF is significantly lower than the STMEF: between 2.9% at peak viewing times to 74% at 9 a.m (blue bar chart).

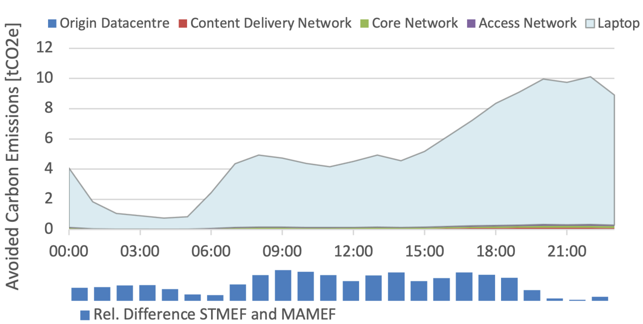

Fig. 3. Short-Term Avoided Carbon Emissions from per Time of Day, over 1 Month (stacked area chart), for social VoD on laptop viewing in the UK using Simplified Thermal MEF. The bar chart shows the difference in emissions between STMEF and Hourly Month-Average MEF.

5. DISCUSSION AND CONCLUSIONS

We evaluate a reduction of the video resolution on UGC video in the UK over one month, with a short-term marginal. Previous work mixed attributional and marginal methods. Our findings are plausible when compared to specific elements of previous studies. Our results show that user devices are most affected by the chosen intervention, which is consistent with existing assessments, e.g. [2, 12, 19]. While, Preist et al. estimate the reduction potential of their intervention to be 2 orders of magnitude higher, they take an attributional approach at global scope over a whole year, including wireless networks and the full range of user devices, using global AEF.

At 0.5gCO2e per person per day, the absolute reduction potential is negligible and highlights the need for more research to support the decarbonisation of digital media. While video streaming constitutes the majority of data traffic in the Internet, and the energy consumption of user devices is substantial (in particular TVs), an attributional approach overestimates the potential reductions of interventions.

Importantly, our short-term perspective does not consider the long-term effects. It is thus not directly applicable to evaluate interventions in a decarbonisation strategy, which must take a long-term marginal view. Our analysis demonstrates a consistent use of marginal indicators, and highlights the discrepancy with an findings from an attributional approach.

The result depends strongly on the chosen MEF, time frames, location, effect size on service resource use (data volume, decoding complexity). Determining the longer-term marginal effects on datacentres, CDNs, networks and user devices requires further research. For example, in our assessment we ignored potential effects from user behaviour change (e.g. viewing time and device choice). This simplifying assumption is a structural effect that needs to be considered. Similarly, the assumed Marginal NEI from Malmodin neglects the structural effects of data transfer on the network infrastructure. More research is required to provide NEI that can be applied in change-oriented assessments. For CDNs, we neglect the effect of reduced storage space requirements from lower bandwidth. Given that attributional assessments show that user devices constitute the majority of the impact, effort For example, in our assessment we ignored potential effects from user behaviour change (e.g. viewing time and device choice). This simplifying assumption is a structural effect that needs to be considered. Similarly, the assumed Marginal NEI from Malmodin neglects the structural effects of data transfer on the network infrastructure. More research is required to provide NEI that can be applied in change-oriented assessments. For CDNs, we neglect the effect of reduced storage space requirements from lower bandwidth. Given that attributional assessments show that user devices constitute the majority of the impact from video streaming, long-term reductions must prioritise them. While bitrate changes will only be able to affect a small part of the overall footprint, more work is necessary to understand the effect of video coding choices on the power consumption of TVs. Our chosen high-end laptop has a particularly high base power consumption. The reduction of power consumption is likely lower on average-spec laptops, tablets and smartphones. We only considered H.265 and UGC. We aim to investigate the saving potential from other codecs, high-quality source, adaptive encoding and VBR. In our assessment we assume all content converts from 1080P to 720P transmission. In practice, UGC is provided in a mix of resolutions. Finally, different MEF exist (see Background); varying by scale, shape, between regions, and over time. Choosing the most appropriate EF is a topic of ongoing research.

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