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An Efficient Energy-Aware Video Service for Smart Devices in Human-Centered Multimedia Systems

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Abstract

Nowadays human-centered multimedia (HCM) systems are growing rapidly, and HCM systems are broadly accessible to users over mobile networks. As one of the most important human-centered computing services, video service constitutes the main part of the overall mobile network traffic in an HCM system. However, video service currently faces significant technical challenges. In particular, despite significant improvements in mobile network bandwidth and processor performance, the online video services on smart devices (e.g., smartphones, tablets) are still constrained by limited battery capacity. This contradiction underscores the inadequacies of existing battery energy consumption optimization strategies in dealing with various usage scenarios, especially in meeting the diverse battery-saving needs of online video stream users. In response to this issue, we have proposed an efficient energy-aware adaptive video service scheme. This scheme divides the battery power into different energy levels, and then dynamically adjusts the playing parameters (including the threshold of the warm-up stage, capacity of the video buffer, etc.) according to the energy level, while helping the edge client to flexibly capture and play back the required videos. Based on designed experiments already conducted on the proposed method, the results demonstrate the effectiveness of this method in optimizing energy consumption for video services.

Keywords

Human-Centered Multimedia Systems, Smart Devices, Video Services, Energy Efficiency, Battery Life

1. Introduction

Nowadays, the world is seeing a rapid pace of technology innovation for human-centered multimedia (HCM) systems, and video-enabled HCM systems can support the smart devices the high-speed mobile broadband network connections. The Groupe Speciale Mobile Association (GSMA) released the 2020 mobile economy statistics report, which announced in 2020 that the mobile industry has occupied almost

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4.7% of global gross domestic product, marking a significant contribution that amounts to over USD 4.1 trillion of economic value over more than 236 countries and regions. In terms of HCM systems, mobile technology development can always attract keen attention not only in economic and industrial development areas, but also in the academic research fields currently. It seems like mobile online video services, considered as important human-centered computing services, shall cover an increasing number of HCM systems in more promising scenarios [1–3]. HCM systems are broadly accessible to users with access to mobile networks. As shown in Fig. 1, the video service provider sends video resources to the edge data center, which then provides video services to various types of users through the base station. Accordingly, the mobile video service plays an increasingly important role in HCM systems.

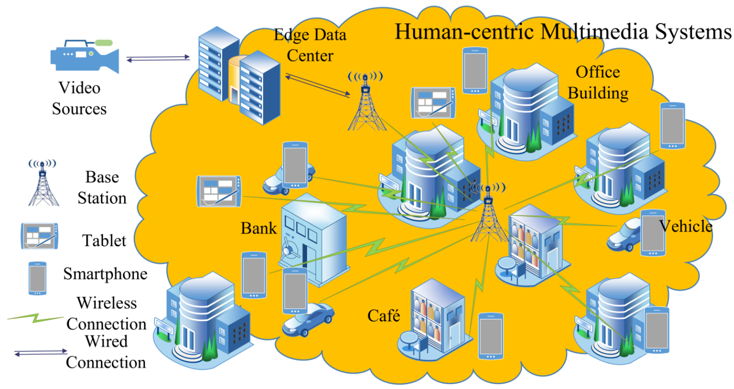

Fig. 1. Video service scenario in HCM systems.

That being said, video service on smart devices currently faces significant challenges, primarily due to limited battery capacity [4–7], despite advancements in mobile network bandwidth and processor performance. This limitation implies the inadequacy of existing battery optimization strategies, especially in meeting the diverse battery-saving needs of online video stream users. For instance, when the remaining battery power of a smart device is sufficient, the user does not need an overly aggressive energy saving strategy, but rather may need a classic video streaming method to reduce the generated network traffic. However, when the smart device battery level is somewhat low, the user needs a more aggressive way to control the battery power consumption. Therefore, implementing energy-aware power optimization strategies can better meet the power-saving requirements of video service users under different battery levels.

To enable video services in the HCM system to accommodate more suitable power-saving strategies under different battery levels, we face the following challenges as described: (1) Way to effectively control the size of the video buffer based on battery level. Intuitively, a larger buffer allows more video segments to be preloaded during the buffering phase, which contributes to energy optimization. However, if the user's current state is in an unstable pattern, which means users may frequently skip or exit the video playing, many video segments in the buffer may be cleared, leading to network bandwidth waste issues. (2) Way to reasonably merge video segment access sessions based on battery level. While merging more video access sessions together can reduce the number of RRC tail, which is a state in mobile communication where the device remains in a high energy consumption mode for a certain period after data transmission has ended, and improve the energy consumption, given unstable user behavior, many "merged" video segments are likely to be discarded from the video buffer, resulting in energy waste. (3) Way to achieve energy reduction based on battery level when the user's behavior pattern is unknown. In a stable pattern, which means users will continuously watch the current video, a larger buffer capacity and merging more video segment access sessions can be adopted to reduce device energy consumption. Alternatively, the opposite is true when the user is in an unstable pattern.

For the sake of addressing these challenges, this paper proposes an efficient energy-aware adaptive video service approach. Firstly, we have divided the remaining battery power of smart devices into different energy levels. Depending on different energy levels, the proposed scheme implements different energy optimization methods for smart devices. The proposed scheme adjusts various parameters of video service and helps users optimize the overall energy consumption under different requirements. In this study, our main contributions are as follows:

- We investigate and analyze the influence factors when dealing with the energy-aware video service scheme.
- An efficient energy-aware self-adaptive video service scheme is proposed for smart devices in HCM systems.
- In comparison to other state-of-the-art approaches, extensive experiments show the efficiency and effectiveness of our proposed video service scheme.

In the remainder of this paper, we survey the related work of our research in Section 2, while in in Section 3, we investigate and analyze the influence factors and energy modeling for smart devices in HCM systems. Then, we propose the efficient energy-aware self-adaptive video service scheme in Section 4. Lastly, in Section 5, we demonstrate the results of tested experiments, and the last section summarizes this work.

2. Related Work

2.1 Online Video Services in HCM Systems

At present, substantial research work has been devoted to online video service technology, and the existing research work mainly discusses general video transmission mode/network design, etc.

The way to improve the quality of real-time video is a research direction of online video services in HCM systems that has received keen attention. Previous research efforts have been dedicated to optimizing the framework of online video services, thus laying a solid foundation for our subsequent research. In [8], a novel adaptive bitrate mechanism was proposed, which can be applied for low-latency online video services. Li et al. [9] revealed that for online video services, the user moving range impacts the engagement in typical short videos but not live video services. For adaptive video streaming, Zhang et al. [10] proposed a new scheme that constructs relay servers in the current infrastructure to provide path diversity for service providers. This scheme is extremely important for us because it provides a potential solution for improving video quality. As for HCM technology, as described in [11–14], incorporating human needs and feedback into system design is of great referential value for us to improve the user experience and system performance.

At the same time, the multimedia service optimization methods and technologies proposed in [15–17], such as combining cloud computing, common sense learning, in addition to blockchain and deep learning, have opened up new research perspectives and problem-solving ideas for us. An AI-based asynchronous video interview platform that can predict interviewees' communication skills and personality traits based on videos was proposed in [18].

2.2 Energy Consumption Optimization of Smart Devices

Energy optimization research for smart devices has always been another topic of keen interest in both the industry sector and academia. Hamzaoui et al. [19] proposed an experimental approach to construct an energy consumption model for mobile applications. The adaptive online video service algorithm proposed by Zhang et al. [20] has enabled smart devices to dynamically and efficiently adjust various parameters to achieve relatively lower energy consumption, thus laying the groundwork for our research. Niemann et al. [21] presented an energy consumption model for smart devices, which estimates the energy consumption of task processing and provides us with a reference model. Yan et al. [22] introduced fuel cell power supply technology and used it to optimize the energy consumption of user smart devices. The energy prediction method based on multi-objective binary grey wolf optimization proposed in [23] has provided us with a new predictive tool. The power adjustment-based cross-layer optimization strategy implemented in [24] achieves a better energy efficiency ratio, offering a potential optimization strategy. The smartphone battery discharge rate model based on machine learning design in [25] demonstrates good prediction efficiency and provides a possible approach for predicting battery consumption.

Additionally, there still is some relevant research work in HCM systems, e.g., network-related optimization algorithms [26–28], new network architectures for information or video transmission [29–31], video data delivery and manipulation [32, 33], data pattern optimization on live video services, mobile services of smart devices, user quality-of-experience optimization for online video services. Although these works have considered many aspects of online video services and energy optimization, most of the studies overlook energy optimization based on energy awareness and different user behavior patterns. In response to this consideration, we have proposed an efficient adaptive energy-aware method. Our proposed method dynamically adjusts video buffer sizes based on battery levels and user behavior patterns, while also intelligently merging cache sessions to achieve energy optimization.

3. Preliminary Study

In this section, we start with a detailed set of energy models, then formally define the energy-aware problem, and finally analyze the main challenges for smart devices in HCM systems.

3.1 In-Depth Energy Modeling for Smart Devices

As discussed in the previous work [20], the overall energy consumption for video service by a smart terminal in mobile environments mainly includes two parts as follows: energy consumption in the buffer prefetching stage and energy consumption in the buffer feeding stage. In the previous study [20], the basic models have been built. In this section, we have considered different actual playback conditions for a more detailed modeling. The user can be in one of two behavior patterns, namely stable pattern and unstable pattern, after starting the online video services on smart devices. A stable pattern means users will continuously watch the current video, which is the most typical behavior for online video services. In this pattern, users do not frequently skip or exit playing. An unstable pattern means users may frequently skip or exit the video playing, which is also another typical behavior. In this pattern, it is necessary to frequently clear the buffer and fetch new video segments. These two patterns almost constitute the majority of cases for online video services, and other complex cases also can be divided into different stages of these two user patterns. Therefore, this work focuses on these two typical user behavior patterns to save on power consumption for online video services. Next, we have built mathematical models for these two patterns, and then transformed the models under different actual conditions. Refer to Table 1 for symbol details in the energy models. In Table 1, “RRC idle” refers to a power-saving state where the mobile device does not maintain a continuous connection in the wireless cellular network.

3.2 Stable & Unstable Patterns

Given the overall energy consumption of smart devices in a stable pattern, the consumption denoted as ζ, consists of two parts. The first part is the energy consumption in the buffer prefetching phase, i.e., $\int_0^{\tau_{bp}} \zeta_{\tau_{bp}} \Delta_t$. The second part is the energy consumption in the buffer feeding phase, i.e., $\frac{n-b_m}{b_m-b_t}\left(\int_0^{\tau_s}\left(\zeta_{\tau_s}-\zeta_0\right) \Delta_t+\int_0^{\tau_i}\left(\zeta_{\tau_i}-\zeta_0\right) \Delta_t\right)$. Note that for the energy consumption of the second part, there are two sub-parts as follows: (i) the energy consumption for network transmission (see the part before the “+” sign); and (ii) the energy consumption during network idle period (see the part after the “+” sign). Accordingly, from the analysis, we can get the following equation as denoted.

Table 1. Notations frequently used in power models

Symbol	Explanation
ζ	Overall network activity energy consumption of d
ζ_0	Average offline power consumption
$\zeta_{\tau(\cdot)}$	Average power consumption in $\tau(\cdot)$
n	Quantity of all video segments
n_i	Quantity of video segments in the ith part in unstable pattern
b_m	Maximum quantity of video segments downloaded in b
b_t	Video segment fetching stage threshold
$\bar{v}_p$	Average downloading speed for buffer prefetching stage
$\bar{v}_f$	Average downloading speed for buffer feeding stage
f_s	File size of each video segment
τ_{bp}	Buffer prefetching stage time duration
τ_s	Service time of each segment
τ_i	Idle period with no video data traffic
τ_{rt}	Time duration of RRC tail
τ_{ri}	Time duration of RRC idle
τ_{sd}	Time duration for playing one video segment

$$\begin{aligned}\zeta &= \int_0^{\tau_{bp}} \zeta_{\tau_{bp}} \, \Delta_t + \frac{n-b_m}{b_m-b_t}\left(\int_0^{\tau_s}\left(\zeta_{\tau_s}-\zeta_0\right)\Delta_t + \int_0^{\tau_i}\left(\zeta_{\tau_i}-\zeta_0\right)\Delta_t\right) \\ &= \frac{b_m}{\bar{v}_p}\zeta_{\tau_{bp}} + \frac{n-b_m}{b_m-b_t}\left(\frac{f_s}{\bar{v}_f}(\zeta_{\tau_s}-\zeta_0) + \tau_{rt}(\zeta_{\tau_{rt}}-\zeta_0) + (\tau_{sd}-\frac{f_s}{\bar{v}_f}-\tau_{rt})(\zeta_{\tau_{ri}}-\zeta_0)\right).\end{aligned} \tag{1}$$

We proceed to address the energy modeling for smart devices in an unstable pattern. In this pattern, users may skip between different videos more frequently. Under the assumption of no loss of generality, the number of video skips is denoted as $i-1$; and the playback of the entire video should be separated into i discrete playback sections. Let n_i be the total number of all contained video segments in the i-th section of the video playback. Then, the energy consumption in the buffer prefetching phase is $i \times \int_0^{\tau_{bp}} \zeta_{\tau_{bp}} \, \Delta_t$, and the energy consumption in the buffer feeding phase is $\frac{n_1+\cdots+n_i-b_m\times i}{b_m-b_t}\left(\int_0^{\tau_s}\left(\zeta_{\tau_s}-\zeta_0\right)\Delta_t + \int_0^{\tau_i}\left(\zeta_{\tau_i}-\zeta_0\right)\Delta_t\right)$. Thus, here we can derive the following equation as denoted:

$$\begin{aligned}\zeta = i \times \int_0^{\tau_{bp}} \zeta_{\tau_{bp}} \, \Delta_t + \frac{n_1+\cdots+n_i-b_m\times i}{b_m-b_t}\left(\int_0^{\tau_s}\left(\zeta_{\tau_s}-\zeta_0\right)\Delta_t + \int_0^{\tau_i}\left(\zeta_{\tau_i}-\zeta_0\right)\Delta_t\right) \\ = i \times \frac{b_m}{\bar{v}_p}\zeta_{\tau_{bp}} + \frac{n_1+\cdots+n_i-b_m\times i}{b_m-b_t}\left(\frac{f_s}{\bar{v}_f}(\zeta_{\tau_s}-\zeta_0) + \tau_{rt}(\zeta_{\tau_{rt}}-\zeta_0)\right. \\ \left. + (\tau_{sd}-\frac{f_s}{\bar{v}_f}-\tau_{rt})(\zeta_{\tau_{ri}}-\zeta_0)\right).\end{aligned} \tag{2}$$

Finally, we can still get the ultimate mathematical expression of the energy models as denoted:

$$\zeta = \begin{cases} \vDash of\ Eq.1\,, & Stable\ pattern \\ \vDash of\ Eq.2\,, & Unstable\ pattern' \end{cases} \tag{3}$$

where ⊨ represents the right side of the equation. To be specific, our target is to get a minimum value of ζ when the user's energy-saving demand is strong. In the next subsection, based on the energy model, we will present our challenges in terms of battery levels.

4. Energy-Aware Self-Adaptive Scheme

For the sake of technically addressing the challenges that are mentioned in the previous section, our research presents an efficient energy-aware method to decrease the energy consumption for smart devices.

4.1 Overview of Energy-Aware Scheme

In general, our energy-aware scheme involves three major steps as follows. Firstly, the method initializes a series of energy-related parameters, then the video buffer prefetches a group of video sections. Various adjustable parameters will work synergistically to achieve energy consumption optimization. Next, the battery power is divided into different levels, and the video playback parameters is dynamically adjusted according to different energy levels. Finally, based on the corresponding energy level, our energy-aware strategy will guide the edge client to flexibly and intelligently capture and playback the required video segments. The main idea is shown in Fig. 2.

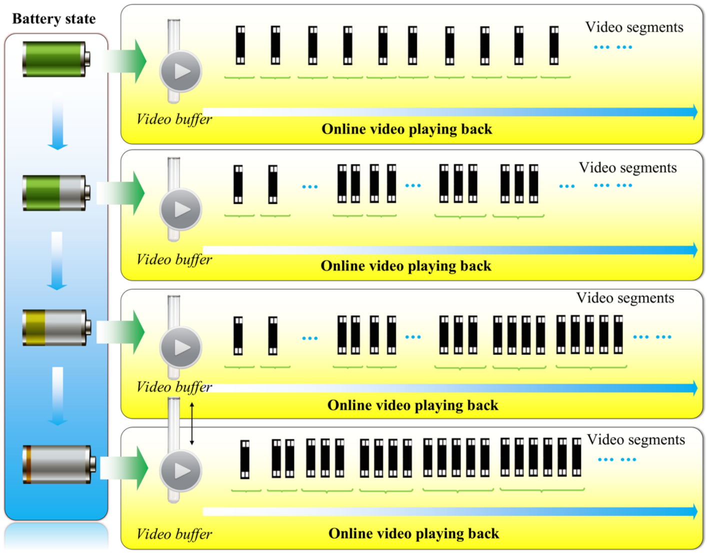

Fig. 2. The main idea of energy-aware scheme.

4.2 Implementation of Energy-Aware Scheme

The energy-aware energy-saving strategy divides battery power from high to low into four energy levels of E-0, E-1, E-2, and E-3. $B_{Ei}$is the i-th battery power threshold to differentiate the energy levels. The notations are shown in Table 2. For the E-0 level, it is deemed that the battery is sufficient and does not need to consider energy saving greatly.

For a traditional online video service player, when the current buffer capacity of the video buffer has not reached the limit, the player will launch another video segment access session. In other words, its default value b_t is equal to $b_m - 1$, where b_m represents the limit of contained video segments in a buffer state In our design, the online video stream player can dynamically adjust b_t. Let $\mho \in [1, \infty)$ be used to differentiate the predefined thresholds for the warm-up phase. In this work, the warm-up phase denotes the beginning stage for playing back the online video. During the warm-up phase, the downloaded video segments in a single video segment downloading session are relatively few. We use “decrement” strategy to adjust the threshold b_t under different power levels.

Table 2. Main notations used in energy-aware scheme

Symbol	Explanation
u_t	Continuous viewing time
b_s	Video buffer size
b_t	Video segment fetching session threshold
Θ	Adjustment threshold of b_s
b'_m	Initial limit of contained video segments in the buffer b
ψ	Adjusting evaluation unit
$\mho$	Warm-up stage threshold
$\top$	Number limit of video segments in a single segment fetching session
Δ	Size adjustment
n_e	Frequency of buffer enlarging
n_e^i	Frequency of buffer enlarging for the i-th playing part in unstable pattern
n_c	Buffered video segment number
B_{Ei}	The i-th battery power threshold to differentiate the energy levels
B_c	Current battery capacity

4.2.1 E-1 energy level

When the user's battery power is at the E-1 level, the user can be considered to be less intense for energy saving. At this point, we have adjusted some parameters related to the playback process to achieve energy saving (i.e., the number of evaluation units ψ, etc.). For b_t, the following adjustment strategies can be constructed as denoted:

$$b_t = b_t - \left\lfloor \frac{\frac{u_t}{\tau_{sd}} - \frac{\psi}{2}(b_m - b_t)(b_m - b_t - 1)}{(b_m - b_t) \times \psi} \right\rfloor. \tag{4}$$

Here $\frac{u_t}{\tau_{sd}}$ is applied to calculate the sum of consecutively watched video segments; $(b_m - b_t) \times \psi$ means that we use the segment video segment downloading session as the evaluation unit; and $(b_m - b_t)(b_m - b_t - 1)$ denotes the total amount of video segments viewed before the last change to b_t, which is obtained from the following expression as denoted:

$$\psi \times \sum_{i=1}^{b_m - b_t - 1} i = \psi \times \frac{\big(1 + (b_m - b_t - 1)\big) \times (b_m - b_t)}{2} = \frac{\psi}{2}(b_m - b_t)(b_m - b_t - 1). \tag{5}$$

4.2.2 E-2 energy level

Under the E-2 level, the user can be considered to have a stronger energy-saving requirement than the E-1 level. At this point, we will further enable and adjust some parameters related to the playback process (i.e., preheating stage thresholds, etc.) to achieve better energy-saving purposes. Under the designed E-2 level, the threshold $\mho$ defined by the warm-up phase will be enabled. Within this threshold, b_t, will be adjusted by the evaluation unit; and after exceeding this threshold, we think that the user is very likely to see the whole video. Consequently, after each video segment downloading session, b_t will be adjusted. At the same time, we have reduced the value of the evaluation unit for each adjustment (from ψ to ψ'). For b_t, it will follow the adjustment strategy as denoted in the equation below:

$$b_t = \begin{cases} b_t - \left\lfloor \dfrac{\frac{u_t}{\tau_{sd}} - \frac{\psi'}{2}(b_m - b_t)(b_m - b_t - 1)}{(b_m - b_t) \times \psi'} \right\rfloor, & if\ (b_m - b_t) < \mho \\ b_t - 1, & otherwise \end{cases} \tag{6}$$

4.2.3 E-3 energy level

Under the E-3 level, it can be considered that the user's device battery is about to run out, and the user has the strongest energy-saving demand. At this point, we will adjust the playback process parameters, such as the video buffer capacity, to meet the highest energy-saving requirements, thus minimizing the energy consumption of mobile devices. In this case, the threshold Ʊ defined by the warm-up phase will be removed. At the same time, the video buffer capacity b_s is changed to b'_s to merge more video segments during the video prefetching phase. After each video segment downloading session is completed, b_t will be changed to get more video segments quicker. b_t follows the adjustment strategy as described below:

$$b_t = b_t - 1. \tag{7}$$

When b_t gradually decreases, more video segments will be downloaded in a single video segment downloading session. Under this circumstance, if the user skips to another section of the video being viewed, it can result in a considerable waste of both power and bandwidth. To mitigate the impact of this problem, our study has introduced a parameter ⊤, which is used to represent the upper limit of the video segment number in a single video segment downloading session.

For traditional online video streaming players, b_s is simply set to a constant value. Let's imagine when the video segment number in a single video segment downloading session is greater than $b_m - b_t$. In this case, the entire online video streaming system would not work properly. To resolve this issue, we have adaptively adjusted b_s in our design. Let $\Theta \in (0,1)$ become the threshold for triggering adjustment b_s, and Δ^* indicate the size of each adjusted capacity.

Specifically, when $\frac{b_t}{b_m} \leq \Theta$, we set $b_s = b_s + \Delta^*$. In addition, when we increase b_s, b_m will naturally increase. Under this circumstance, the amount of video segments in subsequent video segment access sessions may increase dramatically, resulting in other related issues such as bandwidth and energy wastage. To alleviate this problem, when b_s is denoted to be $b_s + \Delta^*$, we directly set $b_t = b_t + \Delta$, where $\Delta = \frac{\Delta^*}{\tau_{sd}}$.

In the normal case, both the number and duration of RRC tails are relatively high. However, by adjusting the value b_t at different power levels, our proposed power-aware energy optimization strategy effectively reduces these metrics. Consequently, our model demonstrates a lower energy consumption compared with the normal case. The effectiveness of our proposed model can be proven through the aforementioned theoretical analysis.

5. Experimental Results & Analysis

5.1 Experimental Configuration

To study the energy consumption of smart equipment when using online video services in HCM systems, we deployed a system platform. This system test platform consists of three main components given as (i) Samsung Galaxy S5, one of the battery-rechargeable Android smartphones; (ii) specialized mobile terminal energy monitors - Monsoon power monitor; and (iii) DASH-IF player, a reference client implementation for online video streaming services. In addition, there are a number of auxiliary components, including Wireshark, QXDM and other professional analytical tools in the designed experiments. Wireshark is used for collecting network data traffic, whereas the QXDM analyzer is used to collect network RRC state information, and the video server is built with Jetty.

We complete the performance evaluation from experiments with four typical example videos given as SL-180, SL-360, SL-720, and SL-1080. Each video length is 600 seconds, with each containing 300 video segments (i.e., video chunks). Every video segment can be played for 2 seconds. Resolutions of these video testing samples are specified as 180p, 360p, 720p, and 1080p. The experimental parameters and specific values are shown in Table 3. The battery life experiment is based on the simulation in which only the video segment downloading process is implemented. When we continuously play the same videos, parameters such as screen power consumption and CPU power consumption generally remain within a stable range. In the same scenarios, the workload of the phone (i.e., decoding and displaying videos) remains, and the required energy should also be constant. In such cases, our focus of energy optimization is on network consumption. Therefore, in the experimental tests, we have minimized the screen brightness to reduce the impact of screen power consumption on the overall energy consumption.

Table 3. Experimental settings

Parameter	Value	Parameter	Value
Δ	5	b_s	20
$\mho$	4	b_s'	30
$\top$	10	B_{E1}	75%
ψ	5	B_{E2}	50%
ψ'	3	B_{E3}	25%
Θ	50%	-	-

We have conducted corresponding experiments on stable and unstable user behavior patterns. If the user skips to another part of the current viewing video, in our evaluation, we have assumed the skip duration in a range from 10 to 50 seconds. If the skip duration exceeds the remaining length of the current video, we assumed that the user has skipped the viewing of this video before the video finishes. In the case that a user has a skip operation in one of the video-playing tests, all other tests will also have a user skip at the same time point. In the unstable pattern tests, we have compared the energy performance of user skip experiments with zero to three skips. It should be noted that zero skips means that no user skips have occurred during video playing back (specifically, the video has been played back in a stable pattern). The competitive strategies and the method we proposed are introduced as follows.

5.1.1 Compared methods

Classic video service: This is the normal and classic way to play back the online videos. When the video buffer does not reach capacity limit, another video section access session will start instantly during the buffer feeding phase.

MF-2 method: The basic idea of this method is to combine two video segment downloading sessions into one. This method can effectively cut down the amount of RRC tails.

MF-4 method: This approach is actually a variant of the MF-2 method above. The main difference compared to the MF-2 is that it combines four video segment downloading sessions into one.

BAC method: This battery adaptive caching strategy will pre-cache video segments as the battery level decreases. This method is derived from the bitrate adaptive method [34]. From E-0 to E-3, the device combines 0, 2, 4, 6 video segment separately when using online video services.

Optimal method: This approach downloads all the video segments in the very first video downloading session, and the received video will be played. This method can minimize the power consumption on the smart devices in HCM systems. Please note that this method is an ideal strategy, but it is not practical for real-world online video services. As such, this method is used primarily for reference purposes and only used in a stable pattern

5.1.2 Energy-aware method

This method allows the video buffer to adjust the playback parameters based on the user’s battery level to achieve energy savings. Refer to the above sections for more details and settings for our design.

5.2 Independent Performance for Each Energy Level Strategy

This part introduces the energy consumption of each independent optimization strategy when playing a single video at different energy levels. Fig. 3 shows the impact of different energy level strategies on the energy consumption of smart devices under different video resolutions. It can be seen that regardless of video resolutions, the more the user video skips, the more energy is consumed by the mobile smart device. The reason is that if the user suddenly starts playing another part of the video, there will be another video buffer prefetching stage. In this case, many unplayed video segments will be eliminated from the video buffer. In fact, these video segments have already taken up extra energy consumption when the downloading is finished. Moreover, we can get that as the number of user video skips increases, the power consumption growth rate of the three energy level strategies is greater than that of the classic video service, namely MF-2 and MF-4 methods. The reason is that in an unstable pattern, the three energy level strategies cannot be maintained in the most energy-saving stage for a long duration. From the experimental results, we can find that the overall energy performance of the three energy level strategies still outperforms the classic video service, namely MF-2 and MF-4. This also proves the effectiveness of our proposed energy level optimization strategies.

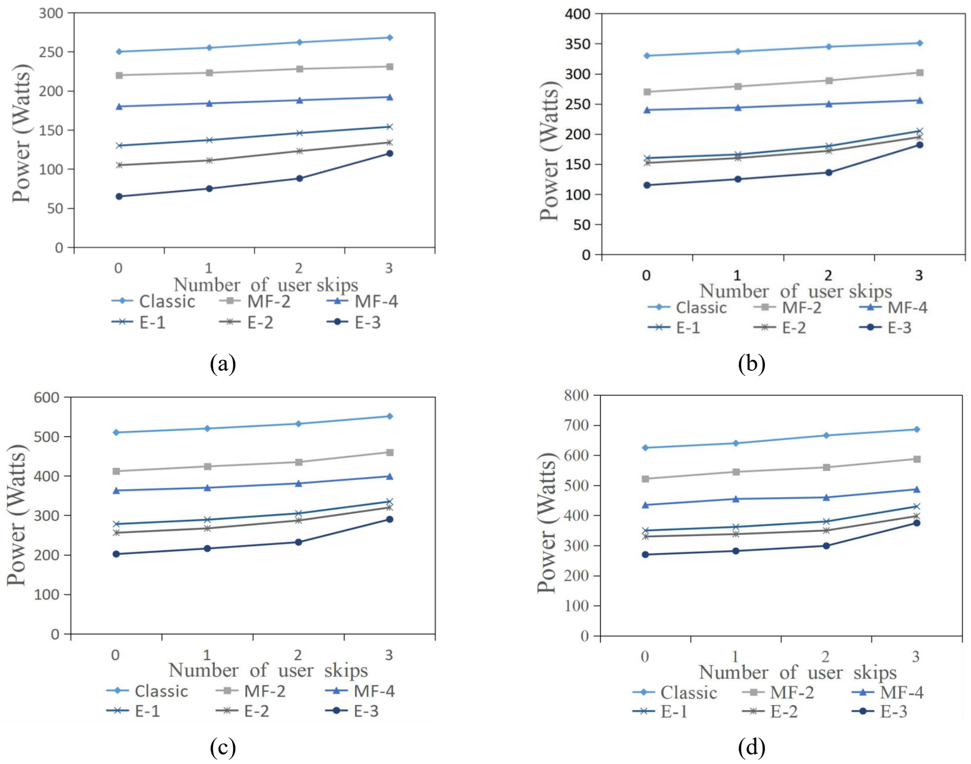

Fig. 3. Impact of different energy level schemes: (a) SL-180, (b) SL-360, (c) SL-720, and (d) SL-1080.

The numbers of video segment downloading sessions of various methods in a stable and unstable pattern are presented in Fig. 4. It can be seen from the figures that even if there is a user skip, the three energy level optimization strategies can achieve a smaller energy consumption in the number of video segment downloading sessions, which is why these three methods can achieve better energy performance. Besides, it can be seen that from the classic video streaming method to the E-3 energy level strategy, the numbers of video segment downloading sessions are almost always declining. This also shows that under the higher energy level optimization strategy, a more aggressive energy-saving method will be adopted to achieve a greater improvement in energy consumption.

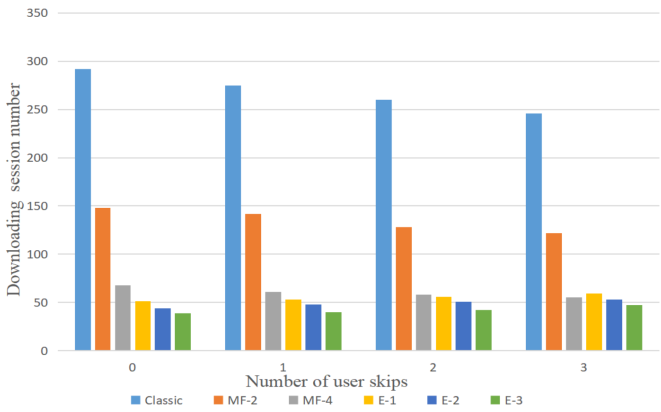

Fig. 4. Numbers of segment downloading sessions under different methods.

5.3 Performance in a Stable Pattern

Fig. 5 shows the comparison of battery life in a stable pattern, where standard normalized data is used for analysis and comparison purposes. According to this evaluation figure, the performance of our proposed energy-aware method is closest to the "optimal" battery life. For the battery life of smart devices, the EA (i.e., energy-aware) method achieves a nearly 20% improvement at all resolutions compared to the classic method. Moreover, we can also see that although the MF-2 and MF-4 methods can extend the battery life of smart devices, the overall optimization level is still lower than the EA method. This result may be attributed to their inability to merge enough video segment downloading sessions (refer to Fig. 4, which shows the numbers of video segment downloading sessions comparison, where 0 means a stable pattern). Note that the video buffer parameters of the MF-2 and MF-4 methods are constant regardless of the user's battery levels. In contrast, the EA method can detect user battery power levels, and the video buffer parameters are adaptively adjusted. Therefore, the EA method can merge more video segment downloading sessions, thus extending the battery life of the smart device.

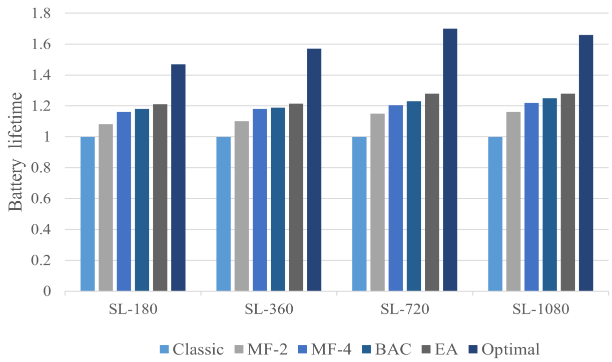

Fig. 5. Battery life comparison in stable pattern.

5.4 Performance in an Unstable Pattern

Fig. 6 shows the comparison of battery life in an unstable pattern, and standard normalized data is also used. It shows that the more frequent the user skips are, the smaller the battery life improvement achieved is. The reason is that if the user skips to another part of the video for playback, there will be another video buffer prefetching phase. Since the classic video service method also expends extra energy during the skip process, the optimization gap is not large in the comparison.

Furthermore, we can see that the battery life of the EA method is greater than that of the classic video stream given as MF-2 and MF-4 methods, under various video resolutions. As such, the lower the resolution is, the smaller the energy improvement. This is because the power consumption from the network part is different under different video resolutions, and the network energy consumption is the focus for optimization. From a performance evaluation, the EA method has better overall performance than classical video service given as MF-2 and MF-4. This also demonstrates the practicality and efficiency of the energy-aware approach proposed in our study.

As with the stable pattern experiment without user skips, we can see the number of video segment downloading sessions for various methods in an unstable pattern from Fig. 4. Even if there are user skips, the EA can still achieve a smaller value in the number of video segment downloading sessions, which also becomes the main reason for the battery life comparison.

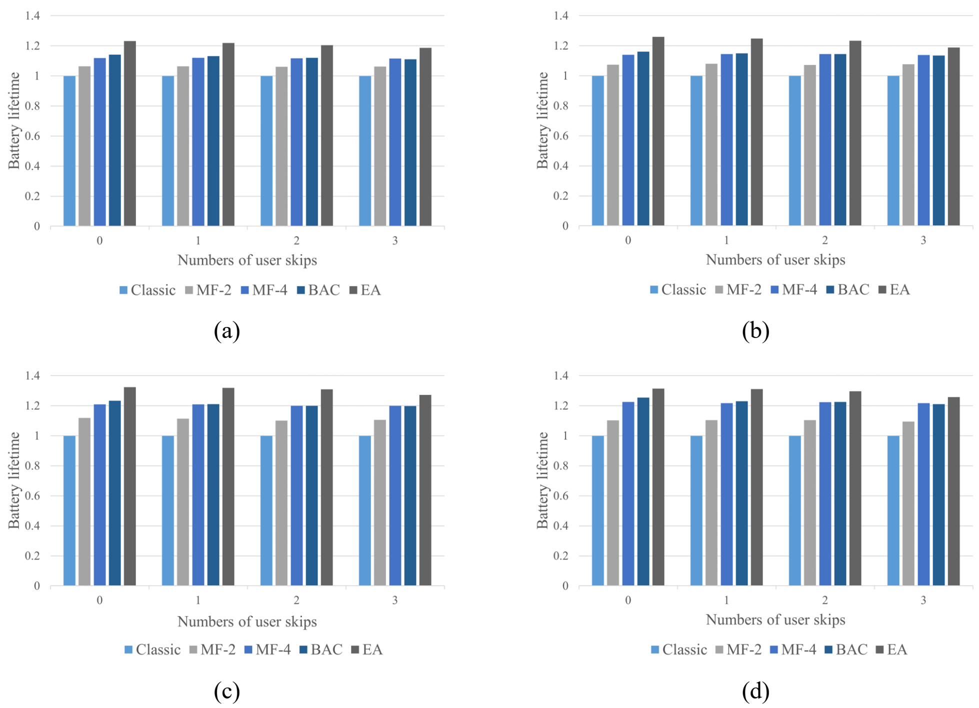

Fig. 6. Battery life comparison in unstable pattern: (a) SL-180, (b) SL-360, (c) SL-720, and (d) SL-1080.

6. Conclusion

Current HCM systems can provide the high-quality video services for various smart devices; however, current battery technology cannot support the video service (i.e., the typical important human-centered computing service) for a long time. Firstly, this paper has investigated new energy consumption challenges for various smart devices over video service scenarios in HCM systems and builds the energy models for different user patterns. Then, we have proposed an efficient energy-aware self-adaptive video service for smart devices. Finally, we have conducted the designed comprehensive experiments for our proposed energy-aware video service scheme. Compared with current existing methods, the experimental results prove the effectiveness and efficiency of our proposed method in both stable and unstable patterns.

In the future, we plan to explore new energy consumption optimization methods for smart devices beyond the video services in HCM systems, and look for new chances to improve the overall energy performance of various connected edge sensors or smart devices.

Author's Contributions

Conceptualization, JZ, YS; Investigation and methodology, MZ, WS; Resources, JZ, YS; Supervision, FA; Writing of the original draft, JZ, YS; Writing of the review and editing, MZ, WS, FA; Formal analysis, MZ, WS; Data curation, JZ, YS. All authors read and approved the final manuscript.

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Competing Interests

The authors declare that they have no competing interests.

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