Power-Efficient Collaborative Distribution of Social Videos over Wireless Community Cloud

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Abstract—**The prevalence of social networking services dramatically changes the landscape of video distribution, in which social video contents spread much faster than traditional video-sharing portals. The pervasive wireless connectivity further enables users to view and generate videos from anywhere at any time. In this paper, we focus on the problem of collaborative distribution of social videos in a wireless community cloud. We aim to minimize the total power consumption of all participants in the community. To this purpose, we first analyze the distribution problem using a Markovian model and study how the soft deadline threshold impacts the total power consumption. We derive the closed-form expression to reveal the relationship between the optimal power allocation strategy and the soft deadline threshold. Our numerical results show that the minimum power consumption increases convexly as the soft deadline threshold approaches one. Moreover, we also observe that when more paths are used for parallel transmission, the total power consumption increases in spite that the power consumption of each individual path is reduced.**

I. Introduction

Social contents have dominated people's online life in the Internet world[1]. The fast spreading nature of social video contents makes it challenging to design an efficient distribution infrastructure[2]. Special content distribution networks are required to guarantee high quality of user experiences, however, it is at the cost of significant infrastructure investment. It is more promising and cost-effective to utilize resources contributed by participants to relieve the deployment burden[3]. In recent years, community cloud[4] emerges a radically new way to realize the sharing of social videos among different participants. A community cloud is constructed by a specific community of users who have shared interests and each user contributes its own resource to serve others. With the penetration of advanced wireless technologies (e.g., LTE, WIFI, WiMax), all participants in a community cloud can be interconnected via high-bandwidth wireless links and such kind of community cloud is referred as *Wireless Community Cloud*.

*The Corresponding Author is Di Wu (*wudi27@mail.sysu.edu.cn*). Yonggang Wen was in part supported by Singapore MOE Tier-1 grant (RG 31/11) and NTU Start-up Grant. Di Wu's work was supported in part by the NSFC, under Grant 61003242, Grant 61272397, the Fundamental Research Funds for the Central Universities, under Grant 12LGPY53, Guangdong Natural Science Funds for Distinguished Young Scholar, under Grant S20120011187, the Program for New Century Excellent Talents in University, under Grant NCET-11-0542, and the Guangzhou Pearl River Sci. & Tech. Rising Star Project, under Grant 2011J2200086.

In a wireless community cloud, there exists a number of collaborative participants (e.g., gateway, Set-top Box), which can be either a resource contributor or resource consumer. Each participant is equipped with a wireless interface for communicating with other participant. Social contents can be shared and distributed among participants through wireless links. To facilitate video sharing in the community, each participant should contribute its storage space for video storage and share the bandwidth of its wireless link. The channel condition of all wireless links in the community cloud is possibly time-varying, and the transmission rate of wireless channels is determined by the power allocation strategy of each participant in the transmission path. The viewing quality of social videos depends on the distribution efficiency over such a wireless community cloud, which is in turn determined by the power allocation strategy of each participant. It is expected to formally study how the user viewing quality is impacted by the power allocation strategy, and how to minimize the total power consumption of all participants while still respecting a certain level of user quality-of-service.

For data transmission over the wireless networks, multi-path transmission technique is widely used to improve the throughput of data transmission (e.g., [5][6][7]). The performance of data transmission can be improved by increasing the efficiency of network resource usage [8][9]. As video distribution is inherently time-sensitive, each video segment is associated with a playback deadline. The viewing quality experienced by users is determined by the probability that each video segment can be transmitted to viewers before its playback deadline. If only considering the hard deadline for each data packet, it is not easy, if impossible, to obtain the exact optimal solution for the optimal power allocation strategy. The minimum power consumption can only be achieved approximately [10][11][12][13]. Instead, the optimal power allocation strategy can be derived deterministically if associating each packets with a soft deadline. By incorporating the user experience as a constraint, the relaxation of using soft deadline can still guarantee the same level of user experience as using the hard deadline.[1]

In this paper, we consider the problem of power-efficient collaborative distribution of social videos in the wireless community cloud. Different from previous studies (e.g.,

[1]An example is illustrated in our technical report[14] to show how to guarantee the same level of user experience.

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[15][16][17][18][19][20]), which only considered online approximate power allocation strategies under the hard-deadline constraint, we design an optimal online power allocation strategy for soft deadline constrained video content distribution over community clouds. To this end, we formulate the power allocation problem with an objective of minimizing the expected power consumption by utilizing the steady state distribution of system states.

Overall, the main contributions of this paper can be summarized as follows:

- We characterize the optimal power allocation strategy under the simplified *ON/OFF* wireless channel model, and find that the optimal power allocation strategy depends on the parameter of the path(i.e., v_{ON}, the *ON* probability) and is homogeneous across parallel transmission paths.
- We investigate the effects of soft deadline threshold when the steady state probability distribution of system states follows a uniform distribution. We prove that the power allocation strategy is homogeneous across system states. We explicitly derive a closed-form solution for the optimal power allocation strategy.
- We conduct numerical studies to show that the minimum power consumption increases convexly as the soft deadline threshold approaches one which indicates significant benefits of using soft deadline. Furthermore, we find that using more parallel transmission paths can reduce the power consumed by each individual path although the total power consumption increases.

The rest of this paper is organized as follows. Section II illustrates the system model and architecture. In Section III we give the formulation of the power consumption optimization problem. We characterize the optimal power allocation strategy in Section IV. Numerical evalution results are presented in Section V. Section VI concludes this paper.

II. System Model and Architecture

A. System Architecture

The sharing of social video contents has been more and more popular among Internet users. Consider a wireless community cloud as illustrated in Fig. 1, users have social connections among themselves, and can share video contents via the underlying wireless links.

When a user creates a video and wishes to share it with others, the video is first replicated multiple times in the community cloud. The replicas are spread over multiple different participants for the redundancy purpose. Here, a participant can be a gateway or STB that represents a user to participate the community cloud. Later, another user who is invited to watch this video can download from multiple participants in parallel. All the participants in the delivery paths collaborate to distribute the video content to the requester. All the data transmissions are based on wireless links.

B. Model Assumptions

The following assumptions are made in our model:

- (A1): Each wireless channel is an i.i.d. block-fading channel, and the channel state will keep unchanged for a short length of time τ_s. We assume no interference exists across wireless channels as collaborative participants are able to use orthogonal frequency bands.
- (A2): Each video is divided into multiple video segments with the same playback duration time T_0. One video segment can not be viewed until being completely downloaded.
- (A3): Each video segment consists of multiple data packets. And the packets of one video segment are evenly distributed on transmission paths. Namely, for one video segment with a size of ω bytes, if the number of available transmission paths is L, then each transmission path needs to transmit ω/L bytes of video data for this video segment.
- (A4): The downloading process of one video segment is synchronous and sequential.

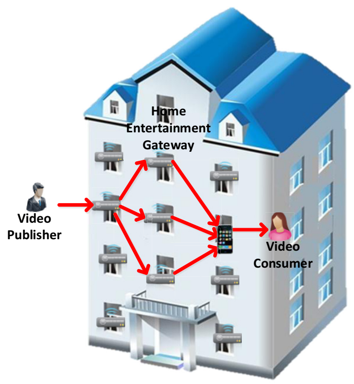


Fig. 1. Social video distribution over a wireless community cloud

Each wireless channel between the resource contributor and the viewer is an i.i.d. block-fading channel. The channel condition can be in any state of $\mathbb{S} = \{s_1, s_2, \cdots, s_N\}$, the corresponding channel gain g is $\mathbb{G} = \{g_1, g_2, \cdots, g_N\}$. The probability distribution of channel state is defined by $\mathbb{V} = \{v_1, v_2, \cdots, v_N\}$. According to Shannon-Hartley theorem[21], the channel capacity R(or achievable transmission rate) along an i.i.d. wireless channel with a bandwidth of W is defined as follows

$$R = W \log_2(1 + \frac{p}{g}), \tag{1}$$

where p is the transmission power of the channel, and g stands for the channel gain. Thus, the probability generating function of the transmission rate of a channel with transmission power p is given by

$$G_R^p(z) = E[z^R] = \sum_{k=1}^{N} v_k \cdot z^{W \log_2(1+\frac{p}{g_k})}. \tag{2}$$

The transmission of one video segment happens synchronously and in parallel among multiple available transmission paths. Fig. 2 illustrates the system state at the beginning of the transmission of one video segment. For each resource contributor, there is a transmission queue which stores video packets of the video segment being transmitted. After all packets of one video segment have been completely transmitted, transmission queues will be filled up by packets of the next video segment. Because the transmission of each video segment is synchronized among all available transmission paths, the occupancy of each transmission queue(in the unit of playback duration time) can not be larger than T_0/L. Denote the occupancy of the playback buffer at time t as $B(t)$(in the unit of playback duration time). From Fig. 2, we can see that the playback deadline of this video segment is $B(t)$ after the beginning of the transmission of this video segment. With assumption (A2), if all the transmission queues can be cleared up within the time period of $B(t)$, then we can claim that this video segment meets its playback deadline.

Soft deadline is defined by the probability that a video segment meets its playback deadline. Without loss of generality, we assume that the playback rate of the downloaded video data is one, the length of time slot τ_s is one time unit and R takes integral values, which indicates that the playback duration time of the video data downloaded along one transmission path within one time slot is an integral. Thus, the occupancy of the playback buffer $B(t)$ is also integral. Denote r_j^i and p_j^i as the transmission rate along path j and the transmission power at the i-th time slot after the beginning of the transmission of this video segment, respectively. Thus, the amount of video data that can be downloaded within $B(t)$ time slots along path j is defined by $\beta_{j,B(t)}(\boldsymbol{p_j}) = \sum_{i=1}^{B(t)} r_j(p_j^i)$, where $\boldsymbol{p_j} = (p_j^1, p_j^2, \cdots, p_j^{B(t)})$. Thus, the soft deadline is defined as follows

$$\prod_{j=1}^{L} Pr(\beta_{j,B(t)}(\boldsymbol{p_j}) \geq \omega/L) \geq \eta, \tag{3}$$

where η represents the soft deadline threshold. Given the probability generating function $G_R^p(z)$, the probability $Pr(\beta_{j,B(t)}(\boldsymbol{p_j}) \geq \omega/L)$ can be expressed as follows

$$Pr(\beta_{j,B(t)}(\boldsymbol{p_j}) \geq \omega/L) = 1 - \sum_{b=0}^{T_0/L-1} \frac{G^{(b)}_{\sum_{i=1}^{B(t)} r_j^i(p_j^i)}(0)}{b!}, \tag{4}$$

where $G_{\sum_{i=1}^{B(t)} r_j^i(p_j^i)}(z)$ is the probability generating function of the random variable $\sum_{i=1}^{B(t)} r_j^i(p_j^i)$. Since the channel states at different time slots are independent, we can calculate $G_{\sum_{i=1}^{B(t)} r_j^i(p_j^i)}(z)$ as follows

$$G_{\sum_{i=1}^{B(t)} r_j^i(p_j^i)}(z) = \prod_{i=1}^{B(t)} G_R^{p_j^i}(z). \tag{5}$$

To simplify the analysis, we make the following additional assumptions:

- (A5): Each wireless channel only has two states: *ON/OFF*. The correspondent channel gain and probability distribution are $\{g_{ON}, g_{OFF}\}$ and $\{v_{ON}, v_{OFF}\}$. Moreover, we assume $v_{ON} > v_{OFF}$.
- (A6): The power allocation strategy only has two choices, that is, $p \in \{0, p^*\}$. What's more, we assume that $W \cdot \log_2(1 + \frac{p^*}{g_{ON}}) = 2$. This assumption can be relaxed by multiplying $W \cdot \log_2(1 + \frac{p^*}{g_{ON}})$ by a constant coefficient, but we assume the coefficient to be one to obtain simpler and explicit mathematical results. And when the channel state is *OFF*, the available transmission rate is 0 no matter what the power allocation strategy is.

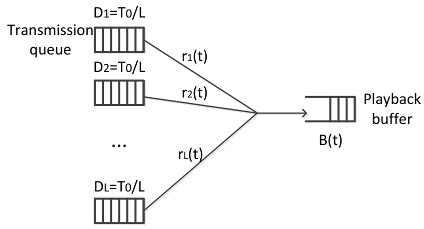


Fig. 2. System state at the beginning of the transmission of one video segment

From (A5) and (A6), we have

$$Pr(\beta_{j,B(t)}(\boldsymbol{p_j}) \geq \omega/L) \quad = 1 - \sum_{k=0}^{M_j} (v_{OFF})^{B(t)-k} \cdot (v_{ON})^k, \tag{6}$$

where $M_j = \sum_{i=1}^{B(t)} I(p_j^i \neq 0)$. We assume that $v_{ON} = \alpha \cdot v_{OFF}$ where $\alpha > 1$, then we have

$$Pr(\beta_{j,B(t)}(\boldsymbol{p_j}) \geq \omega/L) = 1 - (\frac{1-\alpha^{M_j}}{1-\alpha})(v_{OFF})^{B(t)}. \tag{7}$$

III. Problem Formulation

A. Markovian System Model

The system state $\mathcal{S}$ at time t is denoted by a vector $(B(t), \boldsymbol{D(t)})$, where $\boldsymbol{D(t)} = (D_1(t), D_2(t), \cdots, D_L(t))$ represents the occupancy of transmission queues of resource contributors. The playback buffer size is upper bounded by $B > 0$. Thus, we have $0 \leq B(t) \leq B, \forall t$, and $0 \leq D_j(t) \leq T_0/L, \forall j, t$. Note that, we use n as the index of the system state, and during the transition between the nth system state and $n{+}1$th system state, the system state will keep unchanged.

During the transmission of video segment i, the system can be in three different kinds of states:

- (1)$\mathcal{S}_{-1} = (B(n) < T_0, \exists j, 0 < D_j(n) < \frac{T_0}{L}), B(n) + \sum_{j=1}^{L} D_j(n) = T_0$ indicates that a playback buffer starvation happens during the transmission of video segment i. In this state, the playback buffer only stores part of video segment i, and some packets of video segment i stored in some transmission queues have not been transmitted to the viewer. With assumption (A2), there is no available playback video data in the playback buffer.
- (2)$\mathcal{S}_0 = (B(n) = T_0, D_j(n) = \frac{T_0}{L}, \forall j)$ indicates that no playback buffer starvation happens during the transmission of video segment i and the buffered packets of previously transmitted segments have been consumed up when all packets of video segment i have been transmitted.
- (3) $\mathcal{S}_k = (B(n) = T_0{+}k, D_j(n) = \frac{T_0}{L}, \forall j)$ indicates that no playback buffer starvation happens during the transmission of video segment i, and the buffered packets of

previously transmitted segments have not been consumed up when video segment i is completely transmitted.

Note that, the transition from state $\mathcal{S}_{-1}$ to state $\mathcal{S}_0$ represents the re-buffering process. State $\mathcal{S}_{-1}$ can only be transited to state $\mathcal{S}_0$. That is, if $\mathcal{S}_0$ happens during the transmission of segment i, the system state must be $\mathcal{S}_0$ when segment i is completely transmitted. In both state $\mathcal{S}_0$ and $\mathcal{S}_k$, there are available playback video data in the playback buffer and all resource contributors start to transmit video segment $i+1$.

Now, we investigate the transition probabilities between different system states when transmitting segment i:

- $\mathcal{S}_0 \Rightarrow \mathcal{S}_{-1}$. This transition indicates that a buffer starvation happens, which means there is no available video data can be played, before all transmission paths complete transmitting all packets of segment i. The condition $\exists j, 0 < D_j(n+1) < \frac{T_0}{L}$ represents the case in which there is at least one transmission paths having not completed transmitting packets of segment i. The transition probability is defined by $\sum_{j=1}^{L}\sum_{b=0}^{T_0/L-1}\frac{G^{(b)}_{\sum_{i=1}^{T_0} r_j^i(p_j^i)}(0)}{b!} = \sum_{j=1}^{L}\frac{1-\alpha^{M_j}}{1-\alpha}\cdot(v_{OFF})^{T_0}$.
- $\mathcal{S}_0 \Rightarrow \mathcal{S}_0$. This transition indicates that all transmission paths complete transmitting all packets of segment i after the time at which all packets of previously transmitted segments stored in playback buffer are consumed up. The transition probability is defined by $\prod_{j=1}^{L}\frac{G^{(T_0/L)}_{\sum_{i=1}^{T_0} r_j^i(p_j^i)}(0)}{(T_0/L)!} = \prod_{j=1}^{L} C_{M_j}^{T_0/L}\cdot\alpha^{T_0/L}\cdot(v_{OFF})^{T_0}$, if $M_j \geq T_0/L, \forall j$; otherwise, the transition probability is 0.
- $\mathcal{S}_0 \Rightarrow \mathcal{S}_k$. This transition indicates that all transmission paths can complete transmitting all packets of segment i before packets of previously transmitted segments stored in the playback buffer are consumed up. If $k \leq T_0$ and $M_j \geq T_0/L, \forall j$, then the transition probability is defined by $\prod_{j=1}^{L}\frac{G^{(T_0/L)}_{\sum_{i=1}^{T_0-k} r_j^i(p_j^i)}(0)}{(T_0/L)!} = \prod_{j=1}^{L} C_{M_j}^{T_0/L}\cdot\alpha^{T_0/L}\cdot(v_{OFF})^{T_0-k}$, otherwise, the transition probability is 0.
- $\mathcal{S}_{-1} \Rightarrow \mathcal{S}_0$. This transition indicates the re-buffering process. Thus, the transition probability is 1.
- $\mathcal{S}_k \Rightarrow \mathcal{S}_0$. This transition is the same as the transition $\mathcal{S}_0 \Rightarrow \mathcal{S}_0$ while the playback buffer stores more than one video segment before the transition happens. If $M_j \geq T_0/L, \forall j$, the transition probability is defined as $\prod_{j=1}^{L}\frac{G^{(T_0/L)}_{\sum_{i=1}^{T_0+k} r_j^i(p_j^i)}(0)}{(T_0/L)!} = \prod_{j=1}^{L} C_{M_j}^{T_0/L}\cdot\alpha^{T_0/L}\cdot(v_{OFF})^{T_0+k}$, otherwise, the transition probability is 0.
- $\mathcal{S}_k \Rightarrow \mathcal{S}_{-1}$. This transition indicates that a buffer starvation happens before all packets of segment i have been transmitted. The transition probability is defined as $\sum_{j=1}^{L}\sum_{b=0}^{T_0/L-1}\frac{G^{(b)}_{\sum_{i=1}^{T_0+k} r_j^i(p_j^i)}(0)}{b!} = \sum_{j=1}^{L}\frac{1-\alpha^{M_j}}{1-\alpha}\cdot(v_{OFF})^{T_0+k}$.
- $\mathcal{S}_k \Rightarrow \mathcal{S}_{k'}$. This transition indicates that packets of previously transmitted segments have not yet been consumed up before all packets of segment i are transmitted. If $k' \leq k+T_0$ and $M_j \geq T_0/L, \forall j$, then the transition probability is defined as $\prod_{j=1}^{L}\frac{G^{(T_0/L)}_{\sum_{i=1}^{T_0+k-k'} r_j^i(p_j^i)}(0)}{(T_0/L)!} = \prod_{j=1}^{L} C_{M_j}^{T_0/L}\cdot\alpha^{T_0/L}\cdot(v_{OFF})^{T_0+k-k'}$, otherwise, the transition probability is 0.

The system state at the beginning of transmitting one video segment can only be $\mathcal{S}_0$ or $\mathcal{S}_k$, where $k \notin \{-1, 0\}$. There are two kinds of transition paths: one is $\{\mathcal{S}_0, \mathcal{S}_k\} \to \mathcal{S}_{-1} \to \{\mathcal{S}_0, \mathcal{S}_k, \mathcal{S}_{k'}\}$, the other is $\{\mathcal{S}_0, \mathcal{S}_k\} \to \{\mathcal{S}_0, \mathcal{S}_k, \mathcal{S}_{k'}\}$, where $k \neq k' \notin \{1-, 0\}$. An illustrative description of possible system state transitions can be seen in our technical report[14].

The size of the transition probability matrix $\boldsymbol{Q}$ is $(B - T_0 + 2) \times (B - T_0 + 2)$. The one-step transition probability is concluded by the expression (8).

The sequence of system states forms a homogeneous, irreducible, and aperiodic Markov chain. We assume the steady state distribution $\boldsymbol{\pi}$ of system state is well defined. $\boldsymbol{\pi}$ can be obtained by the one-step transition probability

$$\left\{\begin{array}{l} \boldsymbol{\pi} = \boldsymbol{\pi}\boldsymbol{Q}, \\ \sum_{k=-1}^{B-T_0}\pi_k = 1. \end{array}\right. \tag{9}$$

B. Optimization Framework

To reduce the time spent in the re-buffering process, we assume that each channel will allocate the power p^* at time slots when system state is $\mathcal{S}_{-1}$. Thus, the objective problem with an objective of minimizing the power consumed by the distribution network during the transmission of one video segment can be formulated as follows

$$\begin{aligned} \min_{\boldsymbol{M}} \quad & \lim_{t\to\infty} E_{\mathcal{S}_k\in\boldsymbol{\mathcal{S}}}[\sum_{j=1}^{L} M_j(\mathcal{S}_k)p^*] \\ \text{s.t.} \quad & \pi_{-1} \leq \eta, \\ & \boldsymbol{\pi} = \boldsymbol{\pi}\boldsymbol{Q}, \\ & \sum_{k=-1}^{B-T_0}\pi_i = 1, \end{aligned} \tag{10}$$

where $M_j(\mathcal{S}_k) = \sum_{i=1}^{T_0+k} I(p_j^i(\mathcal{S}_k) \neq 0)$ represents the number of time slot that path j should be allocated with power p^*, and $\boldsymbol{M} = \{M_j(\mathcal{S}_k), \forall j, k\}$ denotes the power allocation strategy. The limitation $t \to \infty$ indicates that the expectation is calculated based on the steady state distribution. Note that, when the system state is $\mathcal{S}_{-1}$, the expectation of $M_j(\mathcal{S}_{-1})$ is $\frac{T_0/L}{v_{ON}\cdot W\cdot\log_2(1+\frac{p^*}{g_{ON}})} = \frac{T_0}{2v_{ON}L}$, which is homogeneous across all transmission paths. Thus, the optimal power allocation strategy when the system state is $\mathcal{S}_{-1}$ is $M_j(\mathcal{S}_{-1}) = \frac{T_0}{2v_{ON}L}, \forall j$.

The intuition behind the minimization of power consumption during the transmission of one video segment is two-fold: on one hand, since the transmission power needed by one resource contributor across all of its parallel wireless channels is limited by the hardware. Minimizing the expected power usage for the data transmission of one user can reserve power for other users such that it is possible to optimize performance of data transmission for multiple users[22]; on the other hand,

$$Pr(\mathcal{S}_k \Rightarrow \mathcal{S}_{k'}) = \begin{cases} 1, & \text{if } k=-1, k'=0 \\ 0, & \text{if } k=-1, k' \neq 0 \\ \sum_{j=1}^{L} \frac{1-\alpha^{M_j(\mathcal{S}_k)}}{1-\alpha} \cdot (v_{OFF})^{T_0+k}, & \text{if } k \neq -1, k'=-1 \\ \prod_{j=1}^{L} C_{M_j(\mathcal{S}_k)}^{T_0/L} \cdot \alpha^{T_0/L} \cdot (v_{OFF})^{T_0+k-k'}, & \text{if } k \neq -1, 0 \leq k' \leq T_0+k \end{cases} \quad (8)$$

the power usage during the transmission of video data can translate into energy consumption by resource contributors. Minimizing power usage can prolong the lifetime of resource contributor powered by battery.

IV. Characterizing Optimal Power Allocation Strategy

A. Optimal Power Allocation Strategy

From the definition of steady state distribution, we know that

$$\sum_{k=0}^{B-T_0} \sum_{j=1}^{L} \frac{1-\alpha^{M_j(\mathcal{S}_k)}}{1-\alpha} \cdot (v_{OFF})^{T_0+k} \cdot \pi_k = \pi_{-1}. \quad (11)$$

Lemma 4.1: The optimal power allocation strategy under the simplified *ON/OFF* wireless channel model satisfies that:

$$M_j(\mathcal{S}_k) = M_{j'}(\mathcal{S}_k), \forall \mathcal{S}_k \in \boldsymbol{\mathcal{S}}, j \neq j' \in [1, L]. \quad (12)$$

Proof: See details in technical report[14]. ■

Lemma 4.1 indicates that the optimal power allocation strategy is homogeneous across parallel transmission paths under the simplified *ON/OFF* wireless channel model.

B. Effects of Soft Deadline Threshold

Although it is hard to obtain the closed-form solution for the steady state distribution, we can characterize the effects of soft deadline threshold under specific conditions. We add the following constraints to the power allocation strategy:

- C1: any feasible power allocation strategy can ensure that the steady state distribution of the system state follows a uniform distribution during video viewing process without interruption. That is $\pi_0 - \pi_{-1} = \pi_k, \forall k$.

At first, we'd like to characterize the properties of the power allocation strategy which meets constraint C1.

Lemma 4.2: The constraint (C1) and other constraints in (10) can be satisfied by the following power allocation strategy

$$M(\mathcal{S}_k) = \frac{T_0}{L} \cdot \frac{\sqrt[L]{\frac{1-(v_{OFF})^{T_0-1}}{1-(v_{OFF})^{T_0+1}}}}{1-\sqrt[L]{\frac{1-(v_{OFF})^{T_0-1}}{1-(v_{OFF})^{T_0+1}}}}, \forall k = 0, \cdots, B-T_0$$

Proof: See details in technical report[14]. ■

Denote the optimal power allocation strategy M^* as $M(\mathcal{S}_k)$, that is $M^* = M(\mathcal{S}_k), \forall \mathcal{S}_k \in \boldsymbol{\mathcal{S}} - \{\mathcal{S}_{-1}\}$. We have the following theorem

Theorem 4.3: The optimal power allocation strategy M^* satisfying the constraints in (10) and C1 has the following property

$$M^* = \frac{\ln(G \cdot H + 1)}{\ln \alpha} \quad (13)$$

where $G = \frac{(\alpha-1)\cdot(1-v_{OFF})}{L\cdot((v_{OFF})^{T_0} - (v_{OFF})^{B})}$, and $H = \frac{\eta}{1-\eta}$.

Proof:

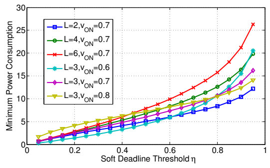
See details in technical report[14]. ■

From Theorem 4.3, we can see that the optimal power allocation is defined by $M_j(\mathcal{S}_{-1}) = \frac{T_0}{2v_{ON}L}, M_j(\mathcal{S}_k) = \frac{\ln(G\cdot H+1)}{\ln \alpha}, k \neq -1, \forall j$. The closed-form optimal power allocation strategy indicates that $M^* \sim \ln G + \ln H$. Note that, $\ln H = \ln \frac{\eta-1}{\eta}$. If a video segment can not meet its payback deadline, then a freezing event will happen. $\frac{\eta}{1-\eta}$ can be considered as the sensitivities to the rate of freezing events. A higher η indicates the user is more sensitive to freezing events. In specific, if $\eta = 0.6$, then the user can tolerant 4 freezing events within 10 time slots, while if $\eta = 0.8$, the user can only tolerate 2 freezing events. When η approaches one, the user will become increasingly sensitive to freezing events, which in turn leads to more power consumption to reduce the probability of freezing events.

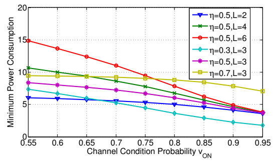
V. Numerical Evaluations

In the beginning, we first evaluate the relationship between the optimal expected power and soft deadline threshold η. The size of each video segment T_0 is 2, and the capacity of playback buffer B is set as 8. We consider two sets of configurations: (a) $v_{ON} \in \{0.6, 0.7, 0.8\}$, $L = 3$; $v_{ON} = 0.7, L \in \{2, 4, 6\}$. The power allocation choice p^* equals to one. We vary the soft deadline threshold η within the interval $(0, 1)$. Fig. 3(a) illustrates the optimal expected power under various value of η. It can be observed that the optimal expected power increases convexly as η approaches to one under various configurations. The increase rate of optimal expected power under the case of $\eta > 0.7$ is much higher than that in the case of smaller η. This indicates significant benefits of using soft deadlines. For example, when $\eta = 0.6$ can guarantee the same level of user experience compared with the hard deadline $\eta = 1$, over half of the power consumption can be reduced. Moreover, we can see that using more transmission paths has higher impacts on the minimum power consumption than channel condition under the case of large η. The difference of minimum power consumption under the three configurations with same v_{ON} is much more significant than that under the other three configurations when $\eta \geq 0.8$.

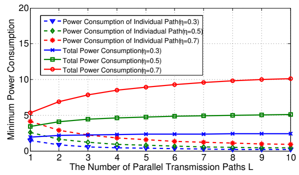
Secondly, we investigate the effects of channel condition. Similar to the first experiment we also consider six different configurations, and vary the probability v_{ON} within the interval $[0.55, 0.95]$. Fig. 3(b) illustrates the optimal expected power under various channel condition. We can see that better channel condition is helpful to reduce power consumption. When the wireless channel condition is good enough(i.e., $v_{ON} \geq 0.8$), the soft deadline threshold η affects the minimum power consumption significantly while the number of transmission paths has rare impacts.



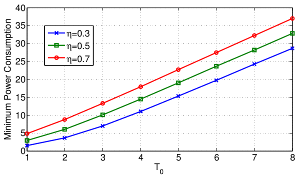
(a) The relationship between the minimum power consumption and soft deadline threshold.



(b) The relationship between the minimum power consumption and channel condition.



(c) The relationship between the minimum power consumption and the number of parallel transmission paths.



(d) The relationship between the minimum power consumption and T_0

Fig. 3. Numerical Evaluation Results

Thirdly, we study the impacts of the number of parallel transmission paths. We set v_{ON} to 0.6, and the soft deadline threshold $\eta \in \{0.3, 0.5, 0.7\}$. Fig. 3(c) shows the minimum power consumption when using various number of transmission paths. We find that the minimum total power consumption increases with the number of transmission paths, while the minimum power consumption of individual path is decreased. Therefore, multi-path data transmission will increase the power consumption of the total distribution network, but the power consumption burden of individual resource contributor will be reduced. The increase of total power consumption will be more significant under a larger soft deadline threshold(i.e., $\eta = 0.7$).

Finally, we investigate the relationship between the minimum power consumption and the playback duration time T_0 of one video segment. Set $\eta \in \{0.3, 0.5, 0.7\}$, $T_0 \in [1, 8]$, and $B = 20$. From Fig. 3(d), we can see that the minimum total power consumption during the transmission of one segment increases linearly with T_0, while the minimum power consumption of unit video data does not increase. Thus, the size of video segments does not impact on the minimum total power consumption during the transmission of the whole video content.

VI. Conclusion

In this paper, we investigate the design of the optimal power allocation strategy for social video distribution over community clouds formed by collaborative resource contributors. The underlying distribution network considered in this paper supports multi-path data transmission and soft deadline constrained content distribution. Under the *ON/OFF* wireless channel model, we show that power allocation strategy depends on the parameter of the path and is homogeneous across parallel transmission paths. Moreover, we obtain a closed-form solution for the relationship between the optimal power allocation strategy and the soft deadline threshold. Numerical evaluations show that a high soft deadline can increase the minimum power consumption convexly. We also show that, by using more parallel transmission paths, we can reduce the minimum power consumption for individual resource contributors, although the total power consumption is increased. In the future, we plan to apply the results obtained in this paper to more general cases, such as general wireless channels.

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