Peer-Assisted Content Distribution Aided by Video Popularity Evolution Model

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***Abstract*—In this paper, we present peer-assisted CDN model, the peer-to-peer networks that can be used to help CDN to deliver streaming media. Our peer-assisted CDN model is aided by Youtube VoD views popularity model called CPPro. We have comparatively evaluated CPPro through trace-driven simulations with synthetic workloads. We use three scenarios in our simulation which are (a) the video popularity in the CPPro system follows the global popularity of the video. (b) the video popularity in the CPPro system is lagged behind the global popularity by several weeks. (c) the video popularity in the CPPro is unrelated to the global popularity. Our results show that CPPro gives lower number of replicas while maintaining same number of peers contribution compare to counterpart work. We also do the significance to the number of replicas using the Kolmogorov-Smirnov statistic on two samples and we find our results are significant ($p - values < 0.1$).**

***Index Terms*—Internet Video on Demand (VoD), P2P, CDN, and Caching.**

I. Introduction

Streaming content, especially video, represents a significant fraction of the traffic volume on the Internet, and it has become a standard practice to deliver this type of content using Content Delivery Networks (CDNs) such as Akamai and Limelight for better scaling and quality of experience for the end users. For example, YouTube uses Google cache and MTV uses Akamai in their operations.

With the spread of broadband Internet access at a reasonable flat monthly rate, users are connected to the Internet 24 hours a day and they can download and share multimedia content. P2P (peer to peer) applications are also widely deployed. In China, P2P is very popular; we see many P2P applications from China such as PPLive, PPStream, UUSe, Xunlei, etc. [1]. Some news broadcasters also rely on P2P technology to deliver popular live events. For example, CNN uses the Octoshape [2] solution that enables their broadcast to scale and offer good video quality as the number of users increases.

From the Internet provider point of view, the presence of so many always-on users suggests that it is possible to delegate a portion of computing, storage and networking tasks to the users, thus creating P2P networks where users can share files and multimedia content. Starting from file sharing protocols, P2P architectures have evolved toward video on demand and support for live events.

Alternatively, video contents can be efficiently distributed on services offered by managed network architectures and CDN companies. The major issues of CDN are high deployment cost and good but not unlimited scalability in the long term. Given the complementary features of P2P and CDN, in recent years some hybrid solutions have been proposed and applied to the operational of CDN [3]–[5] to take the best of both approaches. In Peer assisted CDN, users can download content from CDN nodes from or other users or peers. A user may cache the content after download to serve requests from other users. Due to the complexity of the behavior of peers, the process should be done in the home gateway user where the ISP can control it.

In this work, we will revisit Guo et al.'s, [6] PROP as a basis to evaluate peer-assisted CDN and propose an improvement to the model for the PROP called CPPro. This system is called CPPro abbreviated from out technical term "CDN-P2P Project". We will take Youtube as an example of an Internet VoD service model. In the Youtube service model, we can get data such as (1) the time when a video is uploaded and (2) number of access or number of view. We can get such data using Youtube's API. In seminal work, Borghol et al., [7] used the above information to estimate when a video will become very popular. They divide a video's popularity into three phases: before-peak phase, at-peak phase, and after-peak phase. We will use an estimate of a video's popularity phases for helping PROP. We will explain video popularity in Sec.III. Our contribution is as follows: (1) We use the idea of VoD view popularity model to aid the PROP model. To the best of our knowledge, the combination of the PROP model and the VoD view popularity model is new. (2) From simulation-based experiments, we find that peer contributions in CPPro are almost as good as PROP while the numbers of replicas are lower than PROP resulting in a reduction of resources required.

Our paper presentation as follows: (1) we describe related work in sect.II; (2) we explain detail of Youtube popularity evolution model in sect.III; (3) we explain the caching strategy for CDN and peer in sect.IV; (4) we explain our simulation design, simulator, and its evaluation in sect.V. Finally, we present our conclusions in section VI.

II. Related Work

Content Distribution Networks with peer assist have been successfully deployed on the Internet, such as Akamai [8], [3] and LiveSky [9]. The authors of [8] examine the risks and benefits of peer-assisted content distribution in Akamai and measure the effectiveness of its peer-assisted approach. The authors of [3] conclude from two real world traces that hybrid CDN-P2P can significantly reduce the cost of content distribution and can scale to cope with the exponential growth of Internet video content. Yin et al. [9] described commercial operation of a peer-assisted CDN in China. LiveSky solved several challenges in the system design, such as dynamic resource scaling of P2P, low startup latency, ease of P2P integration with the existing CDN infrastructure, and network friendliness and upload fairness in the P2P operation. Xu et al. [10] used game-theory to show the right cooperative profit distribution of P2P can help the ISP to maximize the utility. Their model can easily be implemented in the context of current Internet economic settlements. Misra et al. [11] also mentioned the importance of P2P architecture to support content delivery networks. The authors use cooperative game theory to formulate simple compensation rules for users who run P2P to support content delivery networks.

The idea of telco- or ISP-managed CDN has been proposed in recent years. The complexity of the CDN business encourages telcos and ISPs to manage their own CDN, rather than allow others to run CDNs on their networks. It has been shown that it is cost effective [12] [13]. Kamiyama et al. [14] proposed optimally ISP operated CDN. Kamiyama et al. mentioned that, in order to deliver large and rich Internet content to users, ISPs need to put their CDNs in data centers. The locations are limited while the storage is large, making this solution effective; using optimum placement algorithm based on real ISP network topologies. The authors found that inserting a CDN into an ISP's ladder-type network is effective in reducing the hop count, thus reduce total link cost. Based on the author definition: Ladder-type network is a network with a maximum degree under 10. Cisco has initiated an effort to connect telco- or ISP-managed CDNs to each other, to form a CDN federation [12] using open standards [15]. They argue that the current CDN architecture is not close enough to the users and ISPs can fill this position.

The idea of utilizing the user's computation power to support ISP operation is not new. The Figaro project [16] proposed the residential gateway as an integrator of different networks and services, becoming an Internet-wide distributed content management for a proposed future Internet architecture [16]. Cha et al., [17] performed trace analysis and found that an IPTV architecture powered by P2P can handle a much larger number of channels, with lower demand for infrastructure compared to IP multicast. Jiang et al. [18] proposed scalable and adaptive content replication and request routing for CDN servers located in users' home gateways. Maki et al., [19] propose traffic engineering for peer-assisted CDN to control the behavior of clients, and present a solution for optimizing the selection of content files. Mathieu et al., [20] are using data gathered from France telecom network to calculate reduction of network load if customers are employed as peer-assisted content delivery.

Guo et al., [6] work's PROP is closest with our work. PROP uses local system (local counter) to calculate the segment popularity in peer-assisted proxy system. PROP uses popularity for proxy cache replacement strategy. In peer side, the author use utility function for cache replacement strategy. A utility function assigns numerical value to outcomes, in such a way that outcomes with higher utility are always preferred of outcomes with lower utilities. In PROP's utility function, the difference between very popular videos and unpopular video is very difficult to differentiate. The utility function is also function from popularity. While the authors successfully show that the results are very good, the peer-assisted system behavior over time is not explain because the author focus on properties such as proxy cache size variations and peer cache size variations. The explanation of the optimal number of replicas is not also clear because unavailable information when the snapshot is taken. In our work, we complement Guo et al., [6] work with VoD viewing popularity evolution model and describe the behavior of the peer-assisted CDN over the time.

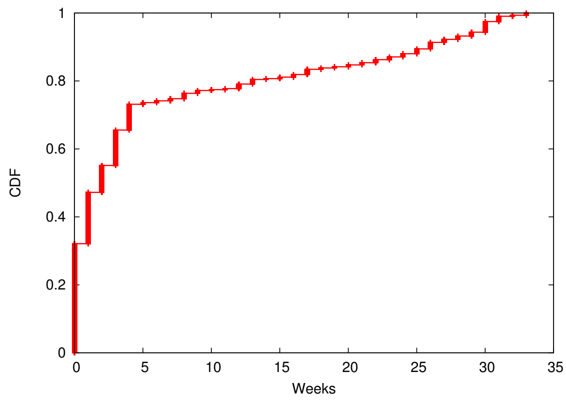


Fig. 1: Time to peak empirical distribution data from [7].

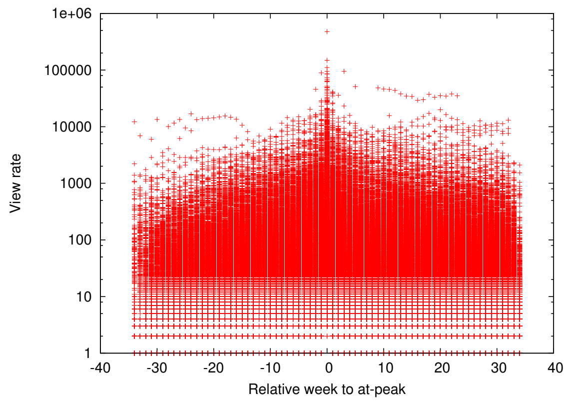


Fig. 2: View rate distribution versus week relative to at-peak phase week for every video, where y-axis in log scale. Every point lies in negative x-axis mean view rate of every video in before-peak phase. Every point lies in x-axis$= 0$ mean view rate of every video at-peak phase. Every point lies in positive x-axis mean view rate of every video in after-peak phase. As we see in this graph, while fig.1 mentioned that 75% of videos reach at-peak within six weeks, we also see that some vides reach at-peak after six weeks. Data from [7].

III. Determining Internet VoD Popularity Phase

The objective of determining the Internet VoD popularity phase is to determine whether a video is at before-peak, at-peak, or after-peak phase, to be used by peers in their caching strategy. For this purpose we use the Youtube content popularity dataset from Borghol et. al., [7] which contains the data of 29791 videos, including the view count and upload time, during 36 weeks of measurements. Figure 1 is cummulative distribution function (CDF) the time-to-peak distribution from Borghol et. al., [7] which shows that around three-quarters of the videos peak within the first six weeks after upload. The time-to-peak is exponentially distributed up-to the sixth week, and it is uniform beyond the sixth week. Borghol et al., [7] define time-to-peak for a video as its age (time since upload) at which its weekly viewing rate is the highest during measurement (from the first week until end of measurement). Because we know the peak time (at-peak phase) of every video, we can also find the before-peak phase and after-phase of every video. For detail we refer the readers to [7].

Suppose a video v in Borghol dataset has a viewing rate $r_v(t)$, $0 <= t < t_f$, and $r_v(t)$ peaks at t_{vp}. The data is transformed by including the relative time-to-peak, such that each data point is a 2-tuple: video rate and relative time to peak, i.e., $rp_v(t) = (r_v(t), tp(t)), tp(t) = t - t_{vp}$. Figure 2 shows the Borghol's dataset with time axis for each video is translated by t_{vp} to the left, such that each video peaks at time 0.

Algorithm 1 Averaging relative weeks from the nearest neighbor points

Require: dataset that consist of weeknumber, viewrate, and relative week to at peak.
$t \leftarrow$ read(weeknumber) {read week number from dataset}
$r_v \leftarrow$ read(viewrate) {read view rate from dataset}
$tp \leftarrow$ read(relativeweeksatpeak) {read relative week at peak from dataset}
t_e {week number of a requested video}
r_e {view rate of a requested video}
$t_e^{before} \leftarrow (t_e - 1)$ {at one week before}
$tp_{before} \leftarrow find\_tp(t_e^{before}, r_e, t, r_v, tp)$
$t_e^{at} \leftarrow (t_e)$ {at same week}
$tp_{at} \leftarrow find\_tp(t_e^{at}, r_e, t, r_v, tp)$
$t_e^{after} \leftarrow (t_e + 1)$ {at one week after}
$tp_{after} \leftarrow find\_tp(t_e^{after}, r_e, t, r_v, tp)$
$tp\_final \leftarrow average(tp_{before}, tp_{at}, tp_{after})$
if $tp\_final < 0$ **then**
  $phase \leftarrow before$
else if $tp\_final == 0$ **then**
  $phase \leftarrow at$
else
  $phase \leftarrow after$
end if

In determining the phase of a requested video e with known age t_e and view rate r_e at t_e, we find the three r_v data points whose rates are closest to r_e at t_e, $(t_e - 1)$, and $(t_e + 1)$, and then average the tp of the three data points. The phase of the requested video e is estimated to be before-peak, at-peak, or after-peak based on whether the average is negative, 0, or positive. The view rate r_e of a video is calculated by substracting the view counts at the time of the current and the previous video requests. The pseudo code for averaging the tp is shown in algorithm 1. But when a video is being requested for the first time, the phase can only be estimated using the age of the video. In this case, we draw 36 random integer numbers s_i, $0 <= i <= 35$, using the time-to-peak distribution in fig. 1 then calculate the count of each integers between 0 and t_e from the drawn numbers then divide the result by 36, i.e., $estphase = \sum_0^{t_e} \frac{count(i,s)}{36}$. The number 36 come from the duration of measurement and each week has its own probability as we shown in fig. 1. This result represents the estimated phase. From time to peak distribution, 50% of video reach peak within four weeks. At that level, we expect that half of videos may reach at-peak and half of videos are not yet reach at-peak. Therefore we put 0.5 as low threshold. Still from the same time to peak distribution 75% of video reach peak within six weeks, and beyond six week the distribution is considered, it means there are not much additional view count. In other words, beyond six weeks we consider videos reach after-peak phase. Therefore we put 0.75 as high threshold. The pseudo code for this purpose is shown in algorithm 2.

Algorithm 2 Determine phase for the first access a requested video

Require: t_e and time-to-peak distribution
$len \leftarrow 35$
for $i = 0$ to len **do**
  draw integer random number between 0 and 35 respect to time-to-peak distribution: $d \leftarrow draw\_integer\_random\_number()$
end for
$total \leftarrow 0$
for $i = 0$ to t_e **do**
  $total \leftarrow total + count(d, i)$ {counting how many each integer random number and sum those}
end for
$estphase \leftarrow total/36$
if $estphase > 0.75$ **then**
  phase $\leftarrow$ after-peak
else if $estphase \leq 0.75$ and $estphase > 0.5$ **then**
  phase $\leftarrow$ at-peak
else
  phase $\leftarrow$ before-peak
end if

IV. System Description

A. System Overview

The main components of the system are: (1) CDN and (2) peers which are self organized into a P2P overlay network. Each peer in the system has two functionalities. First, a peer is a client that requests a video. Second, a peer is a contributor or share the cached video with other peers in the system.

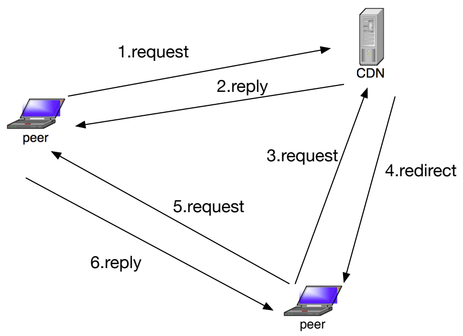


Fig. 3: Peer assisted CDN works as follows: when a peer requests a video, it always goes to a CDN server (step 1). The CDN provides the videos to the peer (step 2). If there is another peer request same video, that request will go to CDN (step 3). A CDN will check its record to see if there is some peers cache that requested video. If there is some peers cache that requested video, a CDN will reply with redirect message that asking a peer to download requested video from other peer (step 4). If there s no peers have requested video, a CDN will serve the video. A peer then can request the video to other peer and get the video (step 5 and step 6).

Peers control the number and utilization of their connection based on current resources availability. In fig.3, we describe the process of a peer that requests a video which derived from PROP. When a video is requested for the first time, the CDN is resposible to deliver the requested video. When a CDN receives a query for a same video, a CDN will find suitable peers that currently have a copy of a requested video. The CDN then returns information about these peers to the querying peer.

B. *Peer caching strategy*

Since we only discuss peer-to-peer side, the caching strategy used in the CDN is out of scope for this project. For the peer replacement strategy, we introduce *utility function* of a video as:

$$u = \frac{(f(p) - f(p_{min}))(f(p_{max}) - f(p))}{r^{\alpha+\beta}} + z(t) \tag{1}$$

where the first term is the utility function from PROP and z is the additional factor for CPPro. p represents the popularity of the video, p_{min} represents minimum popularity in the system, , p_{max} represents maximum popularity in the system, and r represents number of video replica. Following [6], we can calculate p as follows:

$$p = min\left(\frac{n_i^r}{t_i^r - t_a^i}, \frac{1}{t_{cur} - t_i^r}\right) \tag{2}$$

Where n_i^r is number of requested video, t_i^r is last time the video is requested, t_a^i is the uploaded time of the video, and t_{cur} is the current time. To able to track the simulation, we use default value from PROP thus we refer the readers to [6] for the details.

The utility function reflects the popularity of a video in the system that considering number of copy of its video or replica. u value itself lies in interval $[0, 2]$ Guo et al., [6]. We choose video with the smallest utility value as the candidate to be replaced when a peer's cache is full. Since we can determine before-peak phase, at-peak phase, and after-peak phase of video, we modified the original utility function from PROP above by adding a $z(t)$ factor as follows:

$$z(t) = \begin{cases} 0.15 & \text{if phase estimation is before-peak} \\ 0.47 & \text{if phase estimation is at-peak} \\ 0.38 & \text{if phase estimation is after-peak} \end{cases} \tag{3}$$

$z(t)$ is proportion of view count in before-peak, at-peak, and after-peak to the total view count that we get from Youtube datasets. Because from transformed Youtube dataset we already have before-peak, at-peak, and after-peak phase for each video, we can also calculate how many view count in before-peak phase, at-peak phase, and after-peak phase. However at-peak happens only one week and its view count proportion to the total view count relatively small. On the other side, we want to emphasize peer caching of a video during at-peak phase thus proportion of view count of at-peak phase to the total view count is count from one week before at-peak until one week after-peak. Next we can count proportion of view count of before-peak and after-peak to the total view count. The numbers of view count proportion for $z(t)$ is shown in eq.IV-B.

The value of $z(t)$ is assigned after we finish to determine a video popularity phase. For example: if we determine a video popularity phase is at-peak, then we assign $z(t) = 0.47$. In PROP's utility function, the difference between very popular videos and unpopular video is very difficult to differentiate. For an unpopular video, $f(p)$ will be very close to $f(p_{min})$ thus $f(p) - f(p_{min})$ will be very close to 0 then the utility function becomes very small. For a very popular video, $f(p)$ will be very close to $f(p_{max})$, thus $f(p_{max}) - f(p)$ will be very close to 0 and the utility function becomes very small. Linear addition of $z(t)$ factor can help to differentiate the value of utility function.

V. Evaluation

In order to evaluate the proposed peer-caching strategy using our algoritmic designation of the poplarity phase of before-peak, at-peak, and after-peak information from Youtube VoD view model, we have to compare CPPro to the PROP model. We evaluate three metrics, which are: (1) peer contribution to delivery contents during simulation, access frequency of cache during simulation, and number of replicas. We define peer contribution as how many times a video is delivered by peer during simulation. The peer contribution metric is related to the byte-hit-ratio. The byte-hit-ratio is defined as the total bytes of content served by peers normalized by the total bytes of video all peers and the CDN consume. With more peer contributions, we will have higher byte-hit-ratio because peer can get content from other peers. However, because we only interested in peer performance, we compare peer contribution between PROP and CPPro. Contribution ratio of peer (comparing to CDN contribution) is irrelevant in this case. (2) Access frequency of cache reflects the storage utilization. More access means more peer storage utilization. (3) Number of replicas is also related to peer storage utilization. However, too many replicas will waste the storage resources. To evaluate these metrics, we developed a peer-assisted CDN simulator.

A. Simulation Design

This peer-assisted CDN is simulated using an event driven simulation implemented in Python. Peers request videos from a video catalog where the peer request as well as the videos in the catalog are generated using certain distributions.

1) Video Catalog: Each video in tha catalog has the following properties: video-id,size,upload time, final view count, view count function parameters. View count parameters are the distribution parameters. The final view count is the total number of views of a video at the end of simulation and it is generated using uniform distribution. Upload time interval is a Poisson process with $\lambda = 1$. Video size is generated using a uniform distribution. Because of the very weak relationship betwen video size and popularity [21] and because our work focuses on the impact of the popularity aspect on the utility function rather than storage optimization we believe that the choice to assign a random uniform video size from the Youtube dataset does not have an effect to our results. The view rate progression from the upload time until the end of simulation time is modelled using a Beta distribution [7]. As Borghol et al., [7] showed that view rate of a video can be modelled using beta distribution we can calculate α and β parameters. Since we have view rate at peak, we can use Beta distribution mode formula to calculate α or β. In this case, we choose α random uniform between 1 and 3, thus β parameter can be calculated using mode formula.

2) Peer Request Generator: Peers request videos from the catalog using a Poisson process with $\lambda = 1$ [22] for the inter-arrival time. For the requested videos there are three scenarios namely A,B,and C. Scenario A is where the video popularity in the peer-assisted CDN system follows the global popularity of the video. Scenario B is where the video popularity in the peer-assisted CDN system lagging four weeks behind the global popularity of the video. We choose four weeks based on probability from time-to-peak distribution that half of videos are already reach peak within four weeks. Scenario C is where the video popularity in the peer-assisted CDN system does not follow the global popularity of the video. We use Zipf distribution with rate$= 0.9$ for this purpose [23].

3) Simulation Parameters: The simulation parameters are follows:

- Length: 360 days.
- Video size: uniform random between 1MB and 200MB.
- Peer storage capacity: 500MB.
- CDN storage capacity: 10000MB.
- Number of peers: 100000.
- Number of videos: 10000.
- Peer's caching strategy: CPPro, PROP.

Finally, we compare our results to PROP [6] implementation.

B. Result and Discussion

Figure 4 shows the peer contribution in each scenario. Peers are ranked by the number of videos served by each one. They exhibit a similar pattern and only differ in the tails, where CPPro gives higher contributios, which are not significant to the total results as shown in fig. 4a and 4b. However, in the scenario C the peer contribution is almost identical in CPPro and PROP.

The advantage of CPPro to PROP is shown in fig. 5 which show the number of replicas the requested videos at each request event. We see that CPPro result in fewer replicas comparing to those of PROP. Figure 5c that for scenario C, CPPro has much fewer replicas than those of PROP. It shows that many videos are not cached by CPPro. That does not affect the peers contribution comparing to PROP.

Figure 5a, 5b, and 5a show the number of videos replicas available in system when a peer requests a video. As we can see from all figures, the model gives us lower number of replicas than PROP. The model gives lower number of replicas than PROP because when a peer requests a video, that peer is not cached the video. We can see the proportion of cached and not-cached event in table.I. We also present detail of the video phase breakdown in table.II. In model, not-cached events take around 65% from all events and majority of video phase is after-peak for both cached events and not-cached events. Because the majority of video phase is after-peak for both cached events and not-cached events, In PROP, cached events take around 52% from all events for the first scenario and the second scenario, while for the third scenario is 67.7%. In model not-cached events are higher than PROP, means peers do not cached the videos thus we get lower replicas number than PROP.

Denote u_{dl} is the minimum utility function for a video inside the cache and u_{ms} is utility function for a video that will enter the cache, p_{dl} is the popularity for a video inside the cache and p_{ms} is the popularity for a video that will enter the cache. In order a requested video is cached by a peer, the utility function for u_{dl} must be lower than the utility function for u_{ms}.

$$u_{dl} < u_{ms} \tag{4}$$

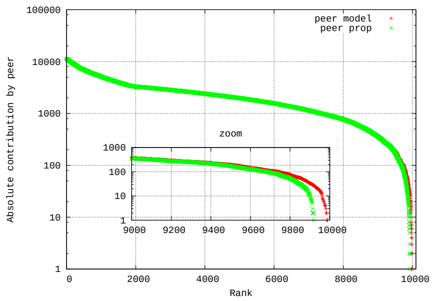
$$\frac{(f(p_{dl}) - f(p_{min}))(f(p_{max}) - f(p_{dl}))}{r_{dl}^{\alpha+\beta}} + z_{dl} < \frac{(f(p_{ms}) - f(p_{min}))(f(p_{max}) - f(p_{ms}))}{r_{ms}^{\alpha+\beta}} + z_{ms} \tag{5}$$

We assume that numbers of replicas are same, thus:

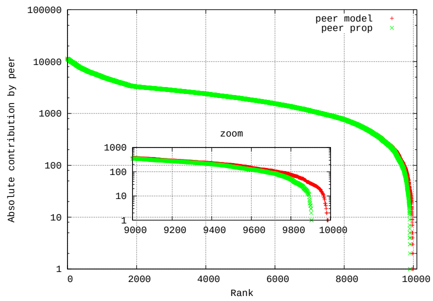
$$(f(p_{dl}) - f(p_{min}))(f(p_{max}) - f(p_{dl})) - (f(p_{ms}) - f(p_{min}))(f(p_{max}) - f(p_{ms})) < z_{ms} - z_{dl} \tag{6}$$

Since p_{min} and p_{max} are same for u_{dl} and u_{ms}, we can arrange the equation become:

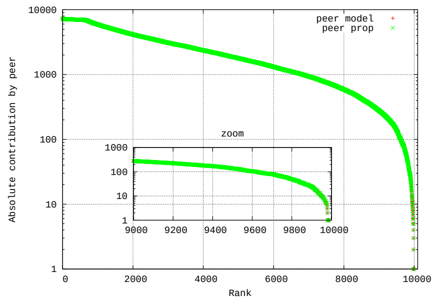
$$f(p_{ms}) - f(p_{dl}) > z_{dl} - z_{ms} \tag{7}$$



(a) Scenario A.

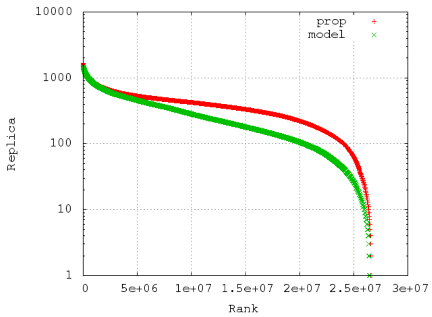


(b) Scenario B.

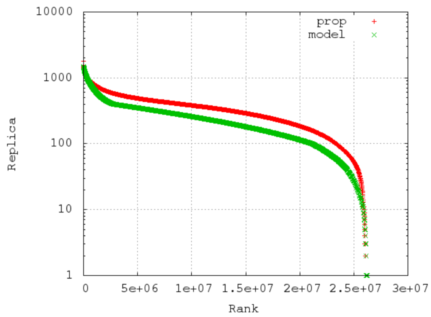


(c) Scenario C.

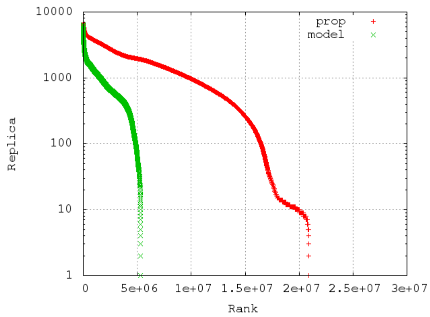
Fig. 4: Absolute peer contributions compared between CPPro and PROP (y-axis in log-scale).



(a) Scenario A.

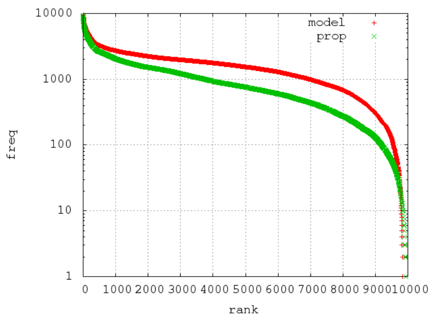


(b) Scenario B.

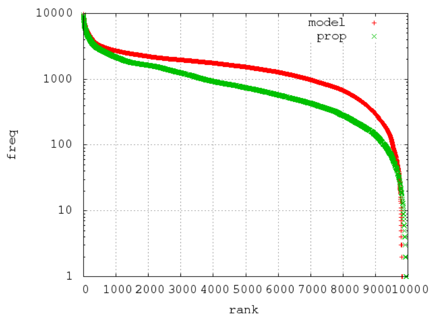


(c) Scenario C.

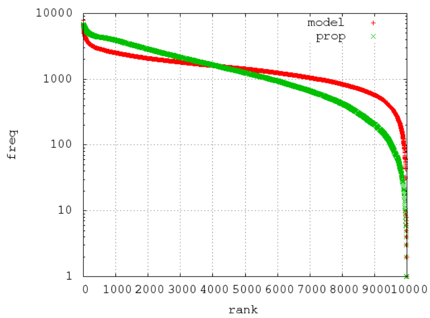
Fig. 5: Comparison of available replicas between model and prop when a peer requests a video (y-axis in log-scale). In scenario C, we found many zero replica when a peer requests a video for CPPro. Because we use log-scale in this figure, the zero numbers can not be viewed



(a) Frequency a video stays in peers for scenario A.



(b) Frequency a video stays in peers for scenario B.

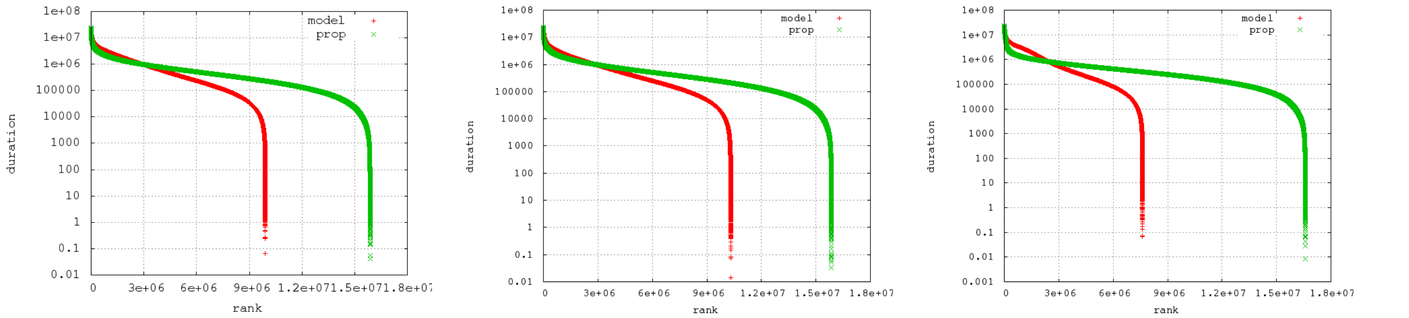


(c) Frequency a video stays in peers for scenario C.

Fig. 6: Frequency a video stays in peers compared between model and prop.

As we know from table.II that the majority of a requested video is after-peak phase and a requested video phase that is at-peak phase is very small portion, then we can see that $z_{dl} - z_{ms}$ term will be in negative term if z_{dl} is before-peak phase or 0 if z_{dl} is after-peak phase. If $z_{dl} - z_{ms} = 0$ then it is same with PROP. Since the not-cached events happen when a requested video phase is after-peak phase, we can get that $f(p_{ms}) - f(p_{dl}) < 0$. For the same situation and we compare to the PROP, the probability of u_{ms} less than u_{dl} in the model is higher than PROP. Therefore, we can see in the model that the events when a peer does not cache a video are more often than PROP.

Figure 6a, 6b, and 6c show the frequency of a video stay in peers compared between model and PROP. As all figure show the model has higher frequency than PROP to stay in peers except for the beginning rank of data where the model has same frequency with prop in first and second scenario. In the third scenario, in the beginning rank of data the model has lower frequency than PROP, then around rank 1000 the model has higher frequency than prop until the end of data.



(a) Cache duration of a video in peers for scenario A.

(b) Cache duration of a video in peers for scenario B.

(c) Cache duration of a video in peers for scenario C.

Fig. 7: Duration compared between model and prop.

TABLE I: Percentage of Cached events and Not-Cached events in CPPro and PROP

Scenario	Type	Cached (times)	Not-Cached (times)	Cached (PetaByte)	Not-Cached (PetaByte)
Scenario A	Model	33.5%	66.5%	2422	4808
	PROP	52%	48%	2416	2230
Scenario B	Model	34.8%	65.2%	2423	4540
	PROP	52.6%	47.4%	2415	2176
Scenario C	Model	32.4%	67.6%	2435.5	5079.5
	PROP	67.7%	32.3%	2435.3	1161.9

TABLE II: Percentage of Video Phase for Model in cached and not-cached events

Scenario	Type/Events	Before-Peak	At-Peak	After-Peak
Scenario A	Model-Cached	8.2%	1.2%	24.1%
	Model-Not-Cached	11.2%	0.8%	54.5%
Scenario B	Model-Cached	6.2%	1.2%	29.8%
	Model-Not-Cached	5.2%	0.8%	56.8%
Scenario C	Model-Cached	8.0%	1.8%	22.7%
	Model-Not-Cached	15.1%	0.8%	51.6%

The frequency a video stay in a video can also be viewed in fig 7a, 7b, and 7c, where in the model some videos have longer cache duration than PROP, while others have shorter cache duration than PROP. Thus, we can see the relationship between cache duration and frequency a video stays in peers.

VI. Conclusion and Future Work

This paper presents a scheme for peer-to-peer network can help CDN to deliver the content over the Internet. We show that by introducing z factor to utility function we can maintain same peer contribution while reducing number of replicas. We found that there are no much different between the first scenario, the second scenario and the third scenario in peer contribution to deliver a video. We found that in the all scenarios, the model gives lower replicas than PROP. This is because in the model, we found that not-cached events are higher than cached events, more specifically, the probability of utility function a requested video in model is lower than PROP. Therefore, in the model the numbers of available replicas are lower than PROP. We also did the significance test to the number of replicas using the Kolmogorov-Smirnov statistic on two samples and we find that for all scenarios the p-values are less than 1% thus the results are significant.

Some areas of improvement that we have identified for future are: The energy trade off this peer-assisted CDN architecture in order to know how much energy saving by ISP and how much increase of energy at users home gateway side in this architecture since we have higher peer contribution. More numerical experiments for other zipf shape parameters.

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