Cloud-Assisted Live Streaming for Crowdsourced Multimedia Content

Fei Chen, *Member, IEEE*, Cong Zhang, *Student Member, IEEE*, Feng Wang, *Member, IEEE*, Jiangchuan Liu, *Senior Member, IEEE*, Xiaofeng Wang, and Yuan Liu

***Abstract*—Empowered by today's rich tools for media generation and distribution, and the convenient Internet access, streaming crowdsourced multimedia content (*crowdsourced streaming*, in brief) generalizes the single-source streaming paradigm by including massive contributors for a video/data channel. It calls a joint optimization along the path from crowdsourcers, through streaming servers, to the end-users to minimize the overall latency. The dynamics of the video sources, together with the globalized request demands and the high computation demand from each sourcer, make crowdsourced live streaming challenging even with powerful support from modern cloud computing. In this paper, we present a generic framework that facilitates a cost-effective cloud service for crowdsourced live streaming. Through adaptively leasing, the cloud servers can be provisioned in a fine granularity to accommodate geo-distributed video crowdsourcers. We present an optimal solution to deal with service migration among cloud instances of diverse lease prices. It also addresses the location impact to the streaming quality. To understand the performance of the proposed strategies in the real world, we have built a prototype system running over the planetlab and the Amazon/Microsoft Cloud. Our extensive experiments demonstrate that the effectiveness of our solution in terms of deployment cost and streaming quality.**

***Index Terms*—Cloud computing, live streaming, crowdsourced multimedia content.**

I. Introduction

THE Internet has witnessed a significant increase in the popularity of media streaming with multi-source channels. In traditional video broadcast, the content of a channel generally comes from a single source, though it could be replicated and then streamed from different servers in a Content Distribution Network (CDN). A *multi-source* system, however, not only serves massive audience worldwide, but its content also comes from multiple contributing sources. For example, since Feb. 17, 2012, NASA Television's Public and Media channels began to transmit their respective content in high definition (HD), with live feeds from such space centers as the NASA Headquarters, the Johnson Space Center, and the Goddard Space Flight Center.[1] With their respective content sources, they collectively serve the users interested in the stories and the latest news from NASA. In the very recent 2014 Sochi Winter Olympics, NBC had a total of 41 live feeds distributed both in Solchi and in the USA,[2] and in FIFA World Cup 2014, when a goal was scored, CBC synchronized the live scenes of the cheering fans in the public squares from a number of cities worldwide in its live streaming channel. The evolution is driven further by today's advanced mobile/tablet devices that can readily capture high quality video anywhere and anytime (e.g. iPhone 6 supports both 60 fps 1080p video recording, and 720 fps slow-motion recording for 720p videos), and such mainstream video sharing platforms as YouTube and Veedme have already enabled multi-party collaborative video content production. All these together are shifting the video service paradigm from the conventional single source, to multi-source, and now toward *crowd source*, in which not only the volumes of multimedia data grow to an extent that the traditional streaming systems cannot handle effectively, but the available video sources for the content of interest also become highly diverse and scalable.

Global streaming imposes high demand on end device capabilities and network connections. The situation is further complicated in a system for streaming crowdsourced multimedia big data (*crowdsourced streaming*, in brief). First, crowdsourced videos are geo-distributed: they come from all over the world, and then spread all over the world. Not only the scale of the consumers is enormous, but also is that of the contributors; Second, the crowdsourcers are often much more dynamic than dedicated content providers, as they can start or terminate a video contribution as their own will. This is particularly true when non-professionals using their smartphones/tablets for video production; Third, for collective content production, massive server capacity is necessary to deal with online video synchronization, processing, and transcoding for highly

Manuscript received February 28, 2015; revised May 31, 2015; accepted July 01, 2015. Date of publication July 23, 2015; date of current version August 10, 2015. This work was supported by the Natural Sciences and Engineering Research Council of Canada (NSERC), by the University of Mississippi under a Start-Up Grant, by Jiangnan University under a Start-Up Grant, by the National Natural Science Foundation of China under Grant 61103223, and by the Natural Science Foundation of Jiangsu Province under Grant BK2011003. An early version of this paper was presented at IEEE INFOCOM 2015, Hong Kong, China, April–May 2015. The guest editor coordinating the review of this manuscript and approving it for publication was Dr. Haohong Wang. *(Corresponding author: Jiangchuan Liu.)*

F. Chen and Y. Liu are with the School of Digital Media, Jiangnan University, Wuxi 214122, China (e-mail: chenf@jiangnan.edu.cn; lyuan1800@sina.com).

C. Zhang and J. Liu are with the School of Computing Science, Simon Fraser University, Vancouver, BC V5A 1S6, Canada (e-mail: congz@sfu.ca; jcliu@cs.sfu.ca).

F. Wang is with the Department of Computer and Information Science, University of Mississippi, Oxford, MS 38677 USA (e-mail: fwang@cs.olemiss.edu).

X. Wang is with the School of Internet of Things Engineering, Jiangnan University, Wuxi 214122, China (e-mail: wangxf@jiangnan.edu.cn).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TMM.2015.2460193

[1][Online]. Available: http://www.nasa.gov/multimedia/index.html

[2][Online]. Available: http://www.istreamplanet.com/sochi-2014/

heterogeneous video contributors and consumers. Generally, comparing with traditional single/multi-source system, more significant effort is needed to collect the highly dynamic and distributed video streams online, and to process/correlate and distribute the live channels to subscribers all over the world.

Elastic resource provisioning and computation offloading are where *cloud computing* platforms excel [14]. We have seen many new generation of cloud-based multimedia services that emerged in recent years, e.g., Netflix, which are rapidly changing the operation and business models in the market. Facing similar scale challenges, live streaming for crowdsourced multimedia big data would benefit from the cloud services, too. Yet the distributed and highly dynamic sources, as well as the much more stringent delay constraints imposed by live streaming, make the problem more involving, which remains to be explored with novel and distinct solutions.

In this paper, using realworld measurement, we identify the potential benefits as well as the key challenges when crowdsourced multimedia big data meets cloud. We present a generic framework for a cost-effective cloud service that provisions cloud resources in a fine granularity to work with geo-distributed video crowdsourcers. Using adaptive and collaborative leasing strategies, our design well accommodates the diverse capacities and prices of cloud instances, and addresses the location impact to the streaming quality. We have built a prototype system running over the Internet and the Amazon EC2/Microsoft Azure cloud, and the experimental results demonstrate the effectiveness of our solution in terms of both deployment cost and streaming quality.

The remainder of this paper proceeds as follows. Section II discusses the background and related work. Section III presents an overview of the proposed cloud assisted live streaming system for crowdsourced multimedia big data, and analyzes its unique challenges using realworld data traces. In Section IV, we first investigate the inherent problem of cloud leasing strategy. An optimal solution is then developed to deal with geo-distributed crowdsourcers in Section V. In Section VI, we present a prototype platform with the measurement results and the trace-driven simulation. Finally, Section VII concludes the paper and discusses potential future directions.

II. Background and Related Work

Empowered by today's rich tools for media generation and collaborative production, and the convenient Internet access, *crowdsourcing* further extends the single-source paradigm. It combines the efforts of multiple self-identified contributors, known as *crowdsourcers*, for a greater result, and has seen success in many areas [3]. For example, LiFS (Locating in Fingerprint Space) was developed for wireless indoor localization with smartphones based crowdsourcing [4]. Ou *et al.* [5] used crowdsourcing approach to optimize mobile devices' energy efficiency by utilizing signal strength traces shared by other devices in cellular networks. For video applications, a scalable system that allows users to perform content-based searches on continuous collection of crowdsourced video was proposed in [7]. Biel *et al.* [6] investigated the the crowdsourcing of personal and social traits in online social video or social media content in general. Recently, Youtube has integrated with Google Moderator, a crowdsourcing and feedback production, to increase the engagement between viewers and content creators. Such other video sharing sites as Poptent and VeedMe have also opened interfaces for crowdsourcers with user generated content. Crowdsourced live streaming services have emerged in the market as well, especially for streaming sports online broadcast. Examples include Stream2Watch.me and sportLEMON.tv.

For large scale distribution, many existing systems rely on content distribution networks (CDNs) [15] or peer-to-peer (P2P) [1], or hybrid solutions [11], [2]. More recently, with the flexible and elastic resource provisioning, cloud computing has been proven to be an efficient solution toward highly scalable video distribution. A prominent example is Netflix, a major on-demand Internet video provider. Netflix migrated its entire infrastructure to the powerful Amazon AWS cloud in 2012, using EC2 for transcoding master video copies to 50 different versions for heterogeneous end users and S3 for content storage [15]. In total, Netflix has over 1 petabyte of media data stored in Amazon's cloud. It leases the computation, bandwidth and storage resources with much lower long-term costs than those with over-provisioned self-owned servers, and reacts better and faster to user demand with the dramatically increasing scale. There have been pioneer studies on migrating video services to the cloud to accommodate worldwide-distributed and time-varying video demands [14], [2]. Aggarwal *et al.* [17] showed that the cost of IPTV services can be noticeably reduced through a cloud infrastructure, and Wu *et al.* [14] utilized a geo-distributed cloud to support large scale social media streaming applications. Wang *et al.* [11] presented CALMS (Cloud-Assisted Live Media Streaming) to lease and adjust cloud server resources in a fine granularity, meeting with the temporal and spatial dynamics of demands from online users.

Our study is motivated by these pioneer works. Yet crowdsourced live streaming demands efficient content collection, processing, and distribution with stringent delay constraints. None of existing algorithms can simultaneously satisfy these design requirements of the resource allocation in the global scale. For example, [8], [12], [18] considered the viewer dynamic in the live streaming systems, without analysis of the demand distribution in the different areas; though [11], [15], [9] deployed the distributed cloud servers or CDNs to handle the dynamic demand in the global scale, crowdsourced live streaming further elevate the challenges with highly dynamic and geo-distributed sourcers; [10], [14] explored the cloud service migration for video-on-demand, while live streaming raises more stringent delay constraint during the server resource allocation; [13] investigated the joint online transcoding and geo-distributed delivery for dynamic adaptive streaming neglecting the price policies of different datacenters. Generally, the resource allocation in crowdsourced live streaming should not only consider both the dynamic viewers and sourcers, but also balance the trade-off between the streaming performance and the system cost. This paper highlights these unique challenges, particularly when crowdsourced live streaming meets cloud, and presents our initial attempts toward addressing these challenges.

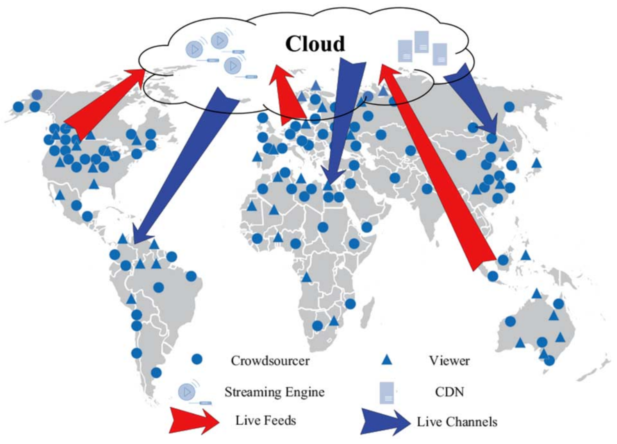


Fig. 1. Generic crowdsourced live streaming system over cloud.

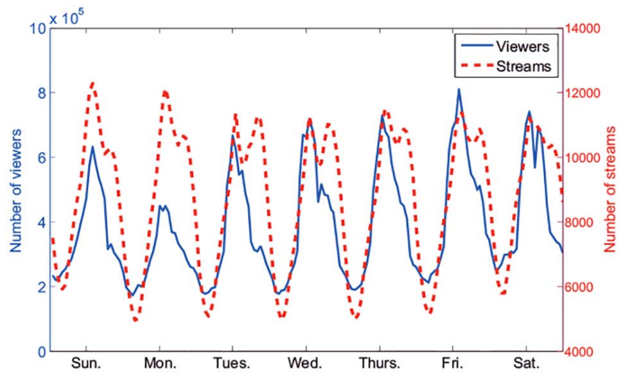


Fig. 2. Number of viewers and source streams variation in one week.

TABLE I
TOP 5 SOURCERS FROM TWITCH.TV ON JULY 12TH

Sourcers ID	Time (Pacific Time)	Location
riotgames	11:10 AM-15:40 PM	Cologne, Germany
dota2ti_ru	7:10 AM-18:10 PM	Seattle, USA
*srkevo*1	6:00 AM-23:40 PM	Las Vegas, USA
riotgamesturkish	1:30 AM-7:10 AM	Istanbul, Turkey
ongamenet	3:00 AM-13:30 PM 18:20 PM-22:40 PM	Seoul, South Korea

III. CROWDSOURCED LIVING STREAMING: SYSTEM OVERVIEW AND CHALLENGES

We illustrate a generic crowdsourced live streaming system with geo-distributed *crowdsourcers* and *viewers* in Fig. 1. A set of crowdsourcers (or *sourcers* in short) upload their individual video contents in realtime, which, through a video production engine, collectively produce a single video stream. The stream is then lively distributed to viewers of interest. Both the sourcers and viewers can be heterogenous, in terms of their network bandwidth, and their hardware/software configurations for video capture and playback. As such, realtime transcoding is necessary during both uploading and downloading, so as to unify the diverse video bitrates/formats from different sourcers for content production, and to replicate the output video stream to serve the heterogeneous viewers, possibly through a CDN with such adaptation mechanisms as DASH (Dynamic Adaptive Streaming over HTTP) [16].

This generic architecture reflects that of state-of-the-art realworld systems. For example, NBC's video content from the 41 feeds in Sochi Winter Olympics were encoded by Windows Azure Media Services to the 1080P format, and dynamically transcoded into HLS and HDS formats. These streams were then pulled from Azure to the Akamai's CDN and distributed to audiences on targeted devices, resulting in over 3000 hours of live Olympics streaming contents.

Given the large system scale and the high bandwidth, storage, and computation demands involved, cloud services with elastic resource provisioning is expected. We again consider a generic geo-distributed cloud infrastructure, which consists of multiple *cloud sites* distributed in different geographical locations (e.g., US East (N. Virginia) and EU (Ireland) in Amazon EC2 Cloud) [14]. Each cloud site resides in a data center, and contains a collection of interconnected and virtualized servers. The server resources will be provisioned for crowdsourced live streaming, e.g., computation resources for collective production and transcoding.

Optimization for conventional single-source video streaming is generally *viewer-driven*; the resource provisioning depends on the distribution of the viewers. In crowdsourced video, however, the sourcers themselves come from all over the world, whose distribution must be as well taken into account during resource provisioning. This is further aggravated given that the collaborative production escalates the demands on both bandwidth and computation. The crowdsourced streaming workflow is also much more dynamic, as individual sourcers can start/terminate based on their own schedules.

To better understand the inherent challenges of deploying such a system, we have crawled one-week trace from July 6 to July 12, 2014 in Twitch.tv website, which is the world's leading video platform and community for gamers,[3] allowing any of its users to broadcast their live streaming videos online through their PCs or PS3/XBOX consoles. It has 14 geo-distributed ingest servers, 1 from Asia area (AS for short), 6 from European area (EU for short), and 7 from United States area (US for short) to serve live broadcast for over 44 million visitors per month in a global scale. For simplicity, we consider that one live stream is contributed by only one sourcer. Fig. 2 shows the number variation of viewers and streams in a week, from July 6 to July 12, 2014. First, it is obvious that the number of viewer is highly dynamic, which is prevalent in current large scale systems [2]. Due to the differences in time zones and languages, the distribution of viewers can be time-varying, which has been discussed in previous works [13], [11]. Similar to the number of viewers, we can see that the number of source streams also has great time variations in one-day time, from about 5000 streams in the early morning to almost 12000 streams in the afternoon. To further investigate the time-varying distribution of the source streams, we have measured the top 15 streams with the highest viewer population from 3:00 AM to 24:00 PM (PST) on July 12, 2014, and list the five most popular streams in Table I. We can see that not only the time periods but also the locations of the stream sourcers are highly dynamic. In Fig. 3, we divide the locations as AS, EU, and US, and record the percentage of

[3][Online]. Available: http://www.twitch.tv/

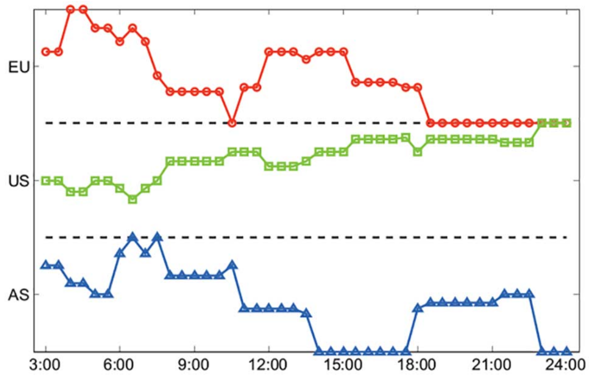


Fig. 3. Source stream distribution in one day.

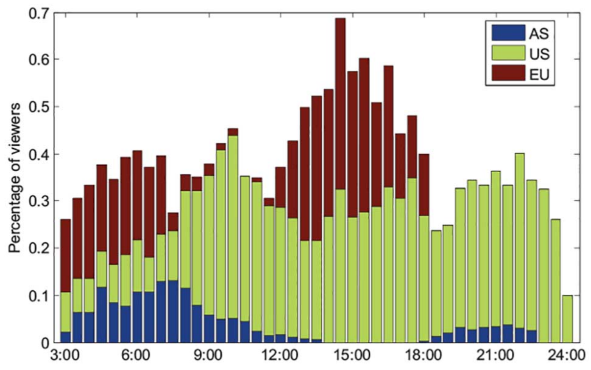


Fig. 4. Viewer demand for the distributed source streams in one day.

source streams from each region for every 30 minutes between 3:00 AM to 24:00 PM. It can be easily observed that most of the streams from Asia and Europe are during the morning and afternoon, and the number of streams from the United States keeps growing when night falls. We further measure the viewer population for the distributed source streams from each region in Fig. 4. We can see that in the early morning between 3:00 AM and 7:00 AM, most of the popular streams come from Europe or Asia. We conjecture that it is because the local times in Europe or Asia are in afternoon or evening, and there are more online sourcers from these regions during that time. Meanwhile, the viewer demand from these areas can also be more active during this period. And most of the viewers may prefer the streams with native language speaking sourcers. Similar reasons can also explain the increase of viewer demand for the source streams from the United States after 15:00 PM.

In summary, in a crowdsourced live streaming system, both the number and the distribution of the crowdsourcers can be highly dynamic. Together with time-varying viewer demand, the conventional server allocation design faces more challenging in a large scale. We will utilize the cloud service to coordinate the crowdsourcers and viewers. The cloud server instances (e.g. EC2 in Amazon Cloud) are provisioned to collect and process the live feeds of the crowdsourcers, and the cloud CDNs (e.g. CloudFront in Amazon Cloud) are deployed to handle the viewer dynamics. Through dynamic cloud leasing, we will present a cost-effective solution with streaming quality guarantee.

TABLE II
NOTATION TABLE

Parameter	Definition
$\mathbb{A}$	The set of n global areas
$\mathbb{S}$	The set of m cloud sites
$\mathbb{L}^A(t)$	The set of sources distributed in different areas
$\mathbb{L}^s(t)$	The set of sources served by different cloud sites
$l_{A_i}(t)$	The live sources from region A_i at time t
$l_{s_j}(t)$	The live sources loaded in cloud site s_j at time t
C^p	The server provisioning cost
c_j^p	The price of leased instances in cloud site s_j
c_0	The cost of a bootstrapping server
C^b	The cost of out-bound traffic from the cloud servers
c_j^b	The price of data traffic in cloud site s_j
C^d	The cost of CDNs deployment
$c_j(\cdot)$	The price policy in cloud site s_j
$Cost_{total}$	The total cost of the streaming system
$Cost_{lease}$	The cloud leasing cost
$P(l_{A_i}(t), s_j)$	Preference of sourcers from $l_{A_i}(t)$ for cloud site s_j
$Index(l_{A_i}(t), k)$	Top k preferred cloud sites for sourcers from $l_{A_i}(t)$
$Cost_{max}$	The total budget of the system
P_{global}	The global relative preference of the crowdsourcers
$\lvert D_{l_{A_i}}(t)\rvert$	The size of viewer demands for live sources $l_{A_i}(t)$
$Cost_{initial}$	The cost with most preferred cloud sites
$\vec{d}(i,j)$	The direction edge from cloud site i to j
$\vec{m}(i,j)$	The service migration vector with l_{A_i} served by s_j
$Deg(i,j)$	The relative preference degradation for $\vec{m}(i,j)$
$Save(i,j)$	The cost saving for migration $\vec{m}(i,j)$
$Lease_{max}$	The budget for cloud leasing strategy

IV. Cloud-Assistance for Crowdsourced Live Streaming

In this section, we first model the global cloud service leasing strategy with quality guarantee, and transform it into an equivalent problem in a directed graph. We will then present an optimal algorithm and an efficient online heuristic solution based on the equivalent problem.

A. Problem Formulation

We present all the parameters and their notations in Table II. We use $\mathbb{A}$ to denote the global areas, which can be divided into n different regions as $\mathbb{A} = \{A_1, A_2, \ldots, A_n\}$. Assume that there are m cloud sites all over the world, represented as $\mathbb{S} = \{s_1, s_2, \ldots, s_m\}$. As most cloud providers have a minimum unit time for the duration of leasing a server (e.g. 1 hour for Amazon EC2), we use T to denote this duration. We define a *time slice* as an integer multiple κ ($\kappa \in \mathbb{N}^+$) of T and at the beginning of each time slice κT, our cloud leasing strategy makes decisions on whether to provision or terminate the cloud servers in the distributed regions. We assume that the schedules of crowdsourced streams are predictable and can be known beforehand, where the rationale is of two folds. First, in practice a large portion of crowdsourced streams are driven by well-scheduled events (e.g. as one of the top 5 sourcers from Twitch.tv in Table I, the channel of $srkevo1$ has a strict schedule about the Evolution 2014 Tournament[4]). Moreover, many self-motivated crowdsourcers prefer a regular broadcast schedule everyday to attract more viewers. We can accordingly forecast the scale of both crowdsourcers and viewers at the next time slice, e.g., using techniques from [11], [18].

[4][Online.] Available: http://evo2014.s3.amazonaws.com/brackets/index.html

For a given time t, we denote the set of source streams from the crowdsourcers as $\mathbb{L}(t)$. According to the location distribution of crowdsourcers, we can specify the set as $\mathbb{L}^A(t) = \{l_{A_1}(t), l_{A_2}(t), \ldots, l_{A_n}(t)\}$ for the n different regions, respectively. As all these live streams are served by the provisioned cloud instances, we further consider the set according to the dedicated cloud sites as $\mathbb{L}^s(t) = \{l_{s_1}(t), l_{s_2}(t), \ldots, l_{s_m}(t)\}$, where $l_{s_j}(t)$ represents the live streaming sources loaded in cloud site s_j. For example, if $l_{s_j}(t) = \emptyset$, no crowdsourced stream is served by cloud site s_j, i.e., cloud site s_j does not need to be leased at time t. Otherwise, if the live streams from area A_2, A_3, and A_5 are served by cloud site s_j, we have $l_{s_j}(t) = l_{A_2}(t) \cup l_{A_3}(t) \cup l_{A_5}(t)$.

We denote the server provisioning cost as $C^p = \sum_{j=1}^m c_j^p(l_{s_j}(t))$, where c_j^p is the price of the leased instances in cloud site s_j. We assume that there is always a bootstrapping server s_0 redirecting the global live sources to the distributed streaming servers with the cost c_0. To offload the bandwidth support for the diverse viewer demands from the cloud servers, a globalized CDN strategy (e.g., CloudFront in Amazon) is deployed to distribute the live streams all over the world. The cost of out-bound traffic from the cloud servers to the CDN can be calculated by the number of channels loaded in the cloud servers, and denoted as $C^b = \sum_{j=1}^m c_j^b(l_{s_j}(t))$. As the cost of the bandwidth support from the CDN to the global viewers is proportional to the viewer demands $D(t) = \sum_{i=1}^n D_{l_{A_i}}(t)$, where $D_{l_{A_i}}(t)$ represents the viewer demands for the crowdsourced streams from region A_i, we can denote the total cost of the CDN as $C^d = c^d(D(t))$ with c^d as the cost to support one unit of the viewer demand. The total cost of the crowdsourced live streaming system can thus be calculated as follows:

$$\begin{aligned} Cost_{total} &= c_0 + C^p + C^b + C^d \\ &= c_0 + \sum_{j=1}^m \left[c_j^p(l_{s_j}(t)) + c_j^b(l_{s_j}(t))\right] + c^d(D(t)) \\ &= c_0 + \underbrace{\sum_{j=1}^m c_j(l_{s_j}(t))}_{Cost_{lease}} + c^d(D(t)) \end{aligned}$$

where $c_j(\cdot)$ can be determined by the price policy of instance leasing and data traffic in cloud site s_j. As the first and last costs on the right side of the equation can not be reduced, we focus on minimizing the middle part of the total cost, i.e., the cloud leasing cost, which we denote as $Cost_{lease}$.

We assume that the live crowdsourcers in each region $l_{A_i}(t)$ have a preference value on a given cloud site s_j, which we denote as $P(l_{A_i}(t), s_j)$. Generally, the preference value can be quantified according to the RTT, jitter or packet loss values of the connections between the crowdsourcers and the given cloud site, such as defined as a concave decreasing function of the estimated latency or a concave increasing function of the estimated connection speed in a geo-distributed service [13]. To guarantee the streaming quality of the crowdsourced streams in region A_i, we only consider allocating these streams to the cloud sites with the top k preference values, and define the set of these cloud sites as $Index(l_{A_i}(t), k)$ for the crowdsourced streams $l_{A_i}(t)$. As a real world example, Twitch/Justin.tv provides an ingest server ranker program to feedback the list with top 3 servers for each crowdsourcer.

The cloud service leasing problem in our geo-distributed crowdsourced live streaming system can thus be formulated as to find a cloud site leasing strategy $\mathbb{L}^s(t)$, subjecting to the following constraints:

1) Cloud site service constraint:

$$\forall A_i \in \mathbb{A}, \exists l_{s_j} \in \mathbb{L}^s, l_{A_i} \subseteq l_{s_j}$$
$$\forall l_{s_j}(t), l_{s_{\hat{j}}}(t) \in \mathbb{L}^s(t),\ \text{if } j \neq \hat{j}, l_{s_j}(t) \cap l_{s_{\hat{j}}}(t) = \emptyset.$$

2) Crowdsourcer preference constraint:

$$\forall A_i \in \mathbb{A}, s_j \in \mathbb{S},\ \text{if } l_{A_i}(t) \subseteq l_{s_j}(t)$$
$$s_j \in Index(l_{A_i}(t), k).$$

3) Total budget constraint:

$$Cost_{lease} + c_0 + C^d \leq Cost_{max}.$$

The cloud site service constraint states that the crowdsourced live streams in a given region are served by only one cloud site. The preference constraint guarantees that the crowdsourced live streams in each region are collected by one of the cloud sites with the corresponding top k preference values. The total budget constraint demands that the total cost including the bootstrapping server, the provisioned cloud sites and the CDN utilization must not exceed the total budget $Cost_{max}$. Our objective is to maximize the *global relative preference* of the crowdsourcers, which is defined as

$$P_{global} = \frac{\sum\limits_{\forall s_j \in \mathbb{S}, l_{A_i} \subseteq l_{s_j}} |D_{l_{A_i}}(t)| \cdot P(l_{A_i}(t), s_j)}{\sum\limits_{\forall A_i \in \mathbb{A}} |D_{l_{A_i}}(t)| P(l_{A_i}(t), Index(l_{A_i}(t), 1))}$$

where for ease of exposition, we also use $Index(l_{A_i}(t), 1)$ to denote the top 1 preferred cloud site for the live crowdsourced streams $l_{A_i}(t)$. We use $|D_{l_{A_i}}(t)|$ to represent the size of viewer demands for crowdsourced streams $l_{A_i}(t)$, and P_{global} is thus a relative ratio ranged between (0, 1] in the global scale.

To make our solution cost-effective, we also need a second objective, i.e., to minimize the cloud leasing cost $Cost_{lease}$. It is easy to see that these two objectives (i.e., P_{global} and $Cost_{lease}$) may contradict with each other, since always leasing the top preferred cloud server can increase the leasing cost. Therefore, we adopt the following linear combination form to align them together by different weights:

$$\frac{p \cdot Cost_{lease}}{Cost_{max} - c_0 - C^d} + q \cdot (1 - P_{global})$$

where p and q are two parameters that can assign different weights to the two goals. As P_{global} is a relative ratio of the preference values of all the crowdsourcers in the system (i.e. if $P_{global} = 1$, all the crowdsourced live streams are allocated in their most preferred cloud sites), $(1 - P_{global})$ should be

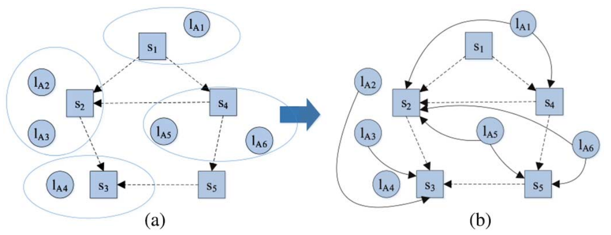


Fig. 5. Illustrative example of (a) the distribution graph and (b) service migration vectors.

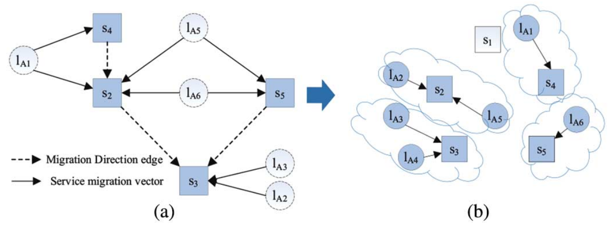


Fig. 6. Illustrative example of (a) a constructed service migration graph and (b) migrated cloud service for geo-distributed crowdsourcers.

minimized as $Cost_{lease}$. To make the leasing cost part also be a ratio ranged between (0, 1], we further divide $Cost_{lease}$ by $(Cost_{max} - c_0 - C^d)$ and then use parameters p and q to linearly combine the two parts together. In the next subsection, we will transform this problem to an equivalent graph problem and then propose an optimal solution.

B. Equivalent Problem

For ease of exposition, we assume the given time is t for the remainder of this section and thus omit (t) in all such notations as $l_{A_i}(t)$, $l_{s_j}(t)$, $D_{l_{A_i}}(t)$, etc. Given the geo-distributed crowdsourcers and cloud sites, we can construct a *distribution graph*. Fig. 5(a) shows an example of 5 cloud sites and global crowdsourcers located in 6 regions. There are two types of vertices in the distribution graph, namely, the live crowdsourcers [e.g. $l_{A_1}, \ldots, l_{A_6}$ in Fig. 5(a)], which are represented by circles, and the cloud sites (e.g. $s_1, \ldots, s_5$), which are represented by squares. Initially, all the live source steams are attached to their most preferred cloud sites and we denote the corresponding leasing cost as

$$Cost_{initial} = \sum_{\forall A_i \in \mathbb{A}, s_j = Index(l_{A_i},1)} c_j(l_{A_i}).$$

According to the price strategy $c_j(\cdot)$ of different cloud site s_j, we have the *direction edges* between these distributed cloud sites. We use $\vec{d}(i,j)$ to denote a direction edge from the cloud site i with higher price to the cloud site j with lower price (e.g. in Fig. 5(a), $\vec{d}$ (4,2) means that $c_2(x) < c_4(x)$ for the same crowdsourcer x), which indicates that the service is migrating towards a more cost-effective solution.

With the distribution graph and direction edges, we then generate *service migration vectors* to indicate the available cloud sites for more cost-effective service migration. We use $\vec{m}(i,j)$ to denote a service migration vector that represents the live crowdsourcers l_{A_i} are migrated and served by the cloud site s_j, rather than the cloud site $Index(l_{A_i},1)$. For example, in Fig. 5(b), the cloud site s_4 is preferred by the live crowdsourcers l_{A_5} and l_{A_6}, i.e., $s_4 = Index(l_{A_i},1)$ for $i \in \{5,6\}$. According to the direction edges $\vec{d}$ (4,2) and $\vec{d}$ (4,5), we can have the service migration vectors $\vec{m}$(5,2) and $\vec{m}$ (5,5) for the live crowdsourcers l_{A_5}, and $\vec{m}$ (6,2) and $\vec{m}$ (6,5) for the live crowdsourcers l_{A_6}. Define M as the set of all service migration vectors that are generated from the given distribution graph. For each service migration vector $\vec{m}(i,j) \in M$, the *relative preference degradation* for live crowdsources l_{A_i} to be served by the cloud site j can be calculated as follows:

$$Deg(i,j) = \frac{|D_{l_{A_i}}|(P(l_{A_i}, Index(l_{A_i},1)) - P(l_{A_i}, s_j))}{\sum_{\forall A_i \in \mathbb{A}} |D_{l_{A_i}}| P(l_{A_i}, Index(l_{A_i},1))}.$$

Also, for each $\vec{m}(i,j)$, we have the *cost saving* as follows:

$$Save(i,j) = c_{\hat{j}}(l_{A_i}) - c_j(l_{A_i})$$

where $c_{\hat{j}}$ is the pricing policy of cloud site $s_{\hat{j}} = Index(l_{A_i},1)$.

Traversing all the service migration vectors $\vec{m}(i,j) \in M$, we can have a *service migration graph* $G(V,E)$. Fig. 6(a) shows an example of Fig. 5(b). We connect the cloud sites with at least one service migration vector through migration direction edges. Note that there may be more than one migration direction edges leaving from the same cloud sites. For example, in Fig. 5(b) there are two migration direction edges $\vec{d}$ (4,2) and $\vec{d}$ (4,5) leaving from cloud site s_4. Since the set of service migration vectors M has already been generated from the migration direction edges, we can put any one of these directed edges into the constructed service migration graph (which is only for the connectivity purpose that will be further explained in the next subsection). Finally, we connect the crowdsourcers to the cloud sites by the service migration vectors. In the constructed service migration graph $G(V,E)$, we can further define the *optimal service migration (OSM)* problem as to find a set of migration vectors $O \subseteq M$, subjecting to the following constraints:

1) Service migration vector constraint:

$$\forall \vec{m}(i,j), \vec{m}(i,\hat{j}) \in M \text{ and } j \neq \hat{j},$$
$$\text{if } \vec{m}(i,j) \in O, \text{then } \vec{m}(i,\hat{j}) \notin O.$$

2) Preference degradation constraint:

$$\forall \vec{m}(i,j) \in O, s_j \in Index(l_{A_i},k).$$

3) Cost saving constraint:

$$Cost_{initial} - \sum_{\forall \vec{m}(i,j) \in O} Save(i,j) + c_0 + C^d \leq Cost_{max}.$$

The service migration vector constraint represents that there is at most one migration vector leaving from a live crowdsourcer vertex, which corresponds to the cloud site service constraint in the cloud leasing problem. The preference degradation constraint is related to the crowdsourcer preference constraint of the cloud leasing problem. The cost saving constraint refers to the total cost not exceeding $Cost_{max}$ in the original problem. Our objective is to minimize the linear combination of cost saving and the relative preference degradation, as seen in the equation at the bottom of the page where $Lease_{max} = Cost_{max} - c_0 - C^d$. As $Cost_{initial}$ cannot be further reduced, our objective can thus be simplified as to minimize

$$\sum_{\forall \vec{m}(i,j) \in O} \left(q \cdot Deg(i,j) - \frac{p \cdot Save(i,j)}{Lease_{max}} \right).$$

The *OSM* problem in graph $G(V,E)$ can be naturally related to the cloud site leasing problem: the optimal solution O indicates the service allocation for the crowdsourcers in each region toward the distributed cloud sites. Fig. 6(b) shows an example with $O = \{\vec{m}(1,4), \vec{m}(3,3), \vec{m}(5,2), \vec{m}(6,5)\}$. Therefore, we have the set of live crowdsourcers served in each cloud site as follows: $l_{s_1} = \emptyset$, $l_{s_2} = l_{A_2} \bigcup_{l_{A_5}}$, $l_{s_3} = l_{A_3} \bigcup_{l_{A_4}}$, $l_{s_4} = l_{A_1}$, and $l_{s_5} = l_{A_6}$.

V. Optimal Cloud Leasing Strategy

The optimal solution can be computed according to the spanning trees in the service migration graph. Clearly, a spanning tree is a subgraph of the directed graph $G(V,E)$. Let T denote the number of spanning trees in a service migration graph $G(V,E)$. We define the set of service migration vectors in the i-th spanning tree as M_i, and the optimal solution of M_i as O_i. We then have the following theorem:

Theorem 1: There must exist an optimal solution O of the service migration vectors M in the service migration graph $G(V,E)$, such that $O \in \{O_1, \ldots, O_T\}$.

Proof: We can prove this using contradiction by assuming that there exits an optimal solution set of the service migration vectors $\acute{O}$ with edges in a circle. According to the definition of service migration graph $G(V,E)$, all the vertices are connected with service migration vectors. There are two scenarios if the edges in directed graph contain a circle: (1) There is more than one directed edge leaving from the same vertex. (2) The directed edges are sequenced in a line one after another, with the end vertex sending toward the head vertex.

1) According to the definition of service migration graph $G(V,E)$, there is at most one migration direction edge leaving a cloud site vertex. As the optimal solution set is a subgraph of $G(V,E)$, $\acute{O}$ does not have more than one direction edge leaving a cloud site vertex. And also, according to the service migration vector constraint, there is at most one service migration vector leaving a live crowdsourcer vertex in the solution set. Therefore, there is no more than one directed edge leaving from the same vertex in $\acute{O}$.
2) Considering the direction edge and the service migration vector, there is no edge sending toward live crowdsourcer in directed graph $G(V,E)$. Thus, there is no live crowdsourcer vertex in the sequenced edges, leaving only direction edges among cloud sites. If these cloud sites are sequenced in a line one after another, we have the following relationship:

$$c_1(l) > c_2(l) > \ldots > c_{end}(l) > c_1(l).$$

Clearly, it leads to a conflict for $c_1(l) > c_1(l)$. Therefore, there is no sequenced edges in a circle in optimal solution set $\acute{O}$.

Therefore, if $\acute{O}$ is an optimal solution set of service migration vectors in directed graph $G(V,E)$, there is no circle in $\acute{O}$. This contradicts with the assumption that $\acute{O}$ has edges in a circle and finishes the proof for the theorem. $\square$

According to Theorem 1, each spanning tree can provide a local optimal solution, and the global optimal solution can be achieved by exploring all the spanning trees in $G(V,E)$. There are extensive studies on enumerating all the spanning trees in a directed graph [19], [20]. E.g., a well-known algorithm in [19] uses backtracking and a method for detecting bridges based on the depth-first search with the time complexity $O(|V| + |E| + |E| \cdot |T|)$ and the space complexity $O(|V| + |E|)$. For a spanning tree i in the service migration graph $G(V,E)$, the service migration vectors M_i (and each of its subsets) are feasible solutions under the service migration vector constraint. By enforcing the preference degradation constraint, a number of spanning trees can be further screened out. Thus, for a remained spanning tree i, we need to calculate the local optimal migration vector set O_i to minimize the combinational objective with the cost saving constraint, which can be solved by the classic 0-1 knapsack problem. In particular, let $\mathbb{F}(ItemSet, TotalWeight)$ denote the standard 0-1 knapsack problem. The $ItemSet$ is M_i in our problem and the $TotalWeight$ is equal to $(\sum_{\vec{m}(i,j) \in M_\lambda} Save(i,j) - Save_{min})$, where $Save_{min} = Cost_{initial} + c_0 + C^d - Cost_{max}$. We thus need to select a set of items $\bar{M}$ (service migration vectors) in the $ItemSet$ (M_i) with the total weight $\sum_{\forall \vec{m}(i,j) \in \bar{M}} Save(i,j) \leq \sum_{\vec{m}(i,j) \in M_\lambda} Save(i,j) - Save_{min}$ so as to maximize the total value

$$\sum_{\forall \vec{m}(i,j) \in \bar{M}} \left(q \cdot Deg(i,j) - \frac{p \cdot Save(i,j)}{Lease_{max}} \right).$$

From the optimal solution $\bar{O}$ of $\mathbb{F}$, we can thus calculate the optimal solution O_i of M_i on the spanning tree i as $O_i = M_i - \bar{O}$.

$$\frac{p}{Lease_{max}} \left(Cost_{initial} - \sum_{\forall \vec{m}(i,j) \in O} Save(i,j) \right) + q \left(1 - (1 - \sum_{\forall \vec{m}(i,j) \in O} Deg(i,j)) \right)$$
$$= \frac{p \cdot Cost_{initial}}{Lease_{max}} + \sum_{\forall \vec{m}(i,j) \in O} \left(q \cdot Deg(i,j) - \frac{p \cdot Save(i,j)}{Lease_{max}} \right)$$

Then the global optimal solution can be found through enumerating all the spanning trees on the service migration graph $G(V, E)$. We summarize this optimal solution in Algorithm 1.

Algorithm 1 Optimal service migration()

```
1. $O = \emptyset$
2. for each enumerated spanning tree $\lambda$ on $G(V, E)$ do
3.   if tree $\lambda$ fulfils the preference degradation constraint then
4.     if $\sum_{\vec{m}(i,j) \in M_\lambda} Save(i,j) \geq Save_{min}$ then
5.       $\bar{O} = \mathbb{F}(M_\lambda, \sum_{\vec{m}(i,j) \in M_\lambda} Save(i,j) - Save_{min})$
6.       $O_\lambda = M_\lambda - \bar{O}$
7.       If $objective(O_\lambda) < objective(O)$ then
8.         $O = O_\lambda$
9.       end
10.    end
11.  end
12. end
13. return $O$ as the global optimal solution for $G(V, E)$
```

It is worth noting that finding the optimal solution for the standard 0-1 knapsack problem can become a time-consuming task as the crwodsourcers are distributed in a large scale, which can cause the optimal solution proposed in Algorithm 1 less suitable in practice, especially for an online system with highly dynamic crowdsourcer distribution and viewer demand. To this end, we further propose a simplified heuristic algorithm in Algorithm 2, which can work efficiently and still return the global optimal solution under certain situations. We then have the following theorem:

Algorithm 2 Efficient online service migration()

```
1. $O = \emptyset$
2. for each enumerated spanning tree $\lambda$ on $G(V, E)$do
3.   if tree $\lambda$ fulfils the preference degradation constraint then
4.     $O_\lambda = \emptyset$
5.     $Total_{save} = 0$
6.     sort $\vec{m}(i,j) \in M_\lambda$ with $\frac{Deg(i,j)}{Save(i,j)}$ in increasing order
7.     for $\vec{m}(i,j) \in M_\lambda$ do
8.       if $(q \cdot Deg(i,j) < \frac{p}{Lease_{max}} \cdot Save(i,j))$ or $(Total_{save} < Save_{min})$ then
9.         put $\vec{m}(i,j)$ into $O_\lambda$
           $Total_{save} = Total_{save} + Save(i,j)$
10.      end
11.    end
12.    if $objective(O_\lambda) < objective(O)$ then
13.      $O = O_\lambda$
14.    end
15.  end
16. end
17. return $O$ as the online solution for graph $G(V, E)$
```

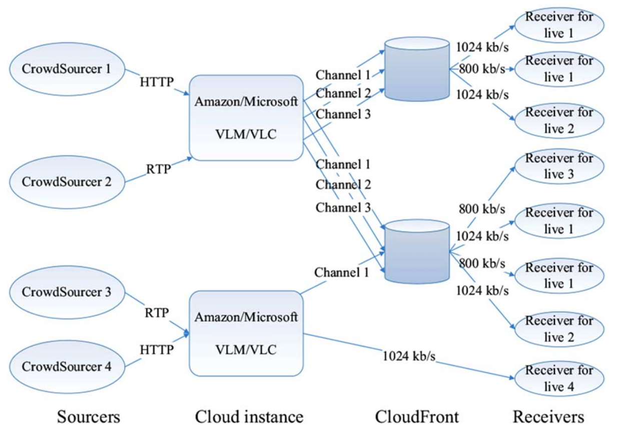


Fig. 7. Prototype implementation of crowdsourced live streaming platform.

Theorem 2: Algorithm 2 can return the global optimal solution when $Cost_{initial} + c_0 + C^d \leq Cost_{max}$ for each enumerated spanning tree.

Note that, if we can prove that the local optimal solution in each spanning tree can be achieved by Algorithm 2 when $Cost_{initial} + c_0 + C^d \leq Cost_{max}$, we can then prove that Algorithm 2 can return the global optimal solution by Theorem 1.

Proof: We can prove this using contradiction by assuming that there is a spanning tree λ with $Cost_{initial} + c_0 + C^d \leq Cost_{max}$ but has an optimal solution $\acute{O}_\lambda \subseteq M_\lambda$, which is better than the solution O_λ found by Algorithm 2. We assume there exists at least one service migration vector $\vec{m}(\acute{i},\acute{j}) \in \acute{O}_\lambda$, with $\vec{m}(\acute{i},\acute{j}) \notin \emptyset_\lambda$ and $Save(\acute{i},\acute{j}) > 0$. As $Save_{min} = Cost_{initial} + c_0 + C^d - Cost_{max} \leq 0$, we always have $Total_{save} \geq Save_{min}$. Thus, for all $\vec{m}(i,j) \in O_\lambda$, we have $q \cdot Deg(i,j) < \frac{p}{Lease_{max}} \cdot Save(i,j)$ and $Save(i,j) > 0$, which mean $\frac{Deg(i,j)}{Save(i,j)} < \frac{p}{q \cdot Lease_{max}}$. As the service migration vectors are sorted with $\frac{Deg(i,j)}{Save(i,j)}$ in increasing order, we have $\frac{Deg(\acute{i},\acute{j})}{Save(\acute{i},\acute{j})} > \frac{Deg(i,j)}{Save(i,j)}$ for $\forall \vec{m}(i,j) \in O_\lambda$. Therefore, if $\frac{Deg(\acute{i},\acute{j})}{Save(\acute{i},\acute{j})} < \frac{p}{q \cdot Lease_{max}}$, we have $\vec{m}(\acute{i},\acute{j}) \in \emptyset_\lambda$, which conflicts with the assumption. Otherwise, if $\frac{Deg(\acute{i},\acute{j})}{Save(\acute{i},\acute{j})} \geq \frac{p}{q \cdot Lease_{max}}$, then we have $objective(O_\lambda) \leq objective(\acute{O}_\lambda)$. This shows that the assumed solution $\acute{O}_\lambda$ is no better than the solution O_λ, and the theorem is proved. □

VI. Performance Evaluation

We have implemented the crowdsourced live streaming system as a prototype based on PlanetLab, Amazon Cloud, Microsoft Azure Cloud, and the opensource VLC/VLM coder, and have conducted realworld experiments to understand its performance. We have also performed trace-driven simulations to further evaluate the system performance in large scale.

A. Prototype Configuration

Fig. 7 shows the implementation of the crowdsourced streaming platform. Initially, the live streaming is started by the broadcast senders through HTTP or RTP live streaming protocols. These live streams will be redirected to the streaming

TABLE III
VIDEOS SOURCE FOR LIVE STREAMING

Videos	Resolution	Codec	Video Bitrate
Birds	1080p	H.264	40 mbps
Monsters	1080p	H.264	10 mbps
Matrix	480p	XviD	1 mbps
Harry Potter	720p	H.264	600 kbps
Shrinkage	720p	H.264	3 mbps

servers in the local area according to a DNS server or load balancer. When the streams are received by the streaming servers, they will be converted into different bit rates through the online transcoding. In order to adjust to the network condition or different types of devices in the end users, one stream can be converted into one or several streams with different bit rates. Finally, the distributed broadcast receivers request the nearby CDNs or servers for the stream with appropriate bit rate to play.

Clients. In our prototype implementation, both the live crowdsourcers and end users are deployed in 398 Planetlab nodes, which are set up with VLC media player `0.8.7Janus` on each node.

Server/CDN. We deploy the federation of cloud service from Microsoft Azure Cloud and Amazon Cloud in our prototype platform. These two cloud service providers can offer totally 21 cloud sites distributed all over the world. In each cloud site, the `General Purpose instances` are provisioned with `Medium(A2)` from Microsoft Azure Cloud and `m3.medium` from Amazon Cloud. Each provisioned instance is set up with `Ubuntu14.04LTS` and installed with VLM to manage multiple live streaming channels. Further, we deploy the CloudFront CDN service in `All Edge Locations` for the globalized content delivery to the geo-distributed viewers. In order to evaluate the streaming quality, the live feeds are generated through videos uploaded from the distributed Planetlab nodes.

Videos. Our prototype platform is effective to redirect current popular IPTV channels with public accessible URLs, such as CNN, BBC World and so on. In order to evaluate the performance (i.e. streaming quality), the live feeds are generated through videos uploaded from the distributed Planetlab nodes. We utilize 5 videos with different bitrates listed in Table III.[5] Each dedicated sourcer stores one of these videos as its own live feed.

Protocols. There are two types of protocols implemented in our platform, namely, RTP streaming and HTTP streaming. Port 5004 is open for RTP, with Port 8081 for HTTP, respectively. These protocols can be set up in the VLM configure file presented in Listing 1.

Listing 1: VLM Configure File

```
new channel1 broadcast enabled
setup channel1 output
#http{mux = ts, dst =: 8081/channel1}
setup channel1 input
"http : //sender_ip_address : 8081"
setup channel1 option http − reconnect
control channel1 play
new channel2 vod enabled
setup channel2 input rtp : //@ : 5004
```

[5][Online]. Available: http://www.cs.sfu.ca/%7Ejcliu/TMM/crowdsourcing/videos

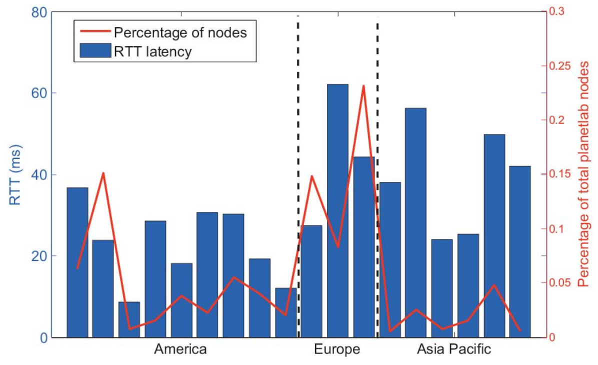


Fig. 8. RTT latency from the top 1 preferred cloud sites.

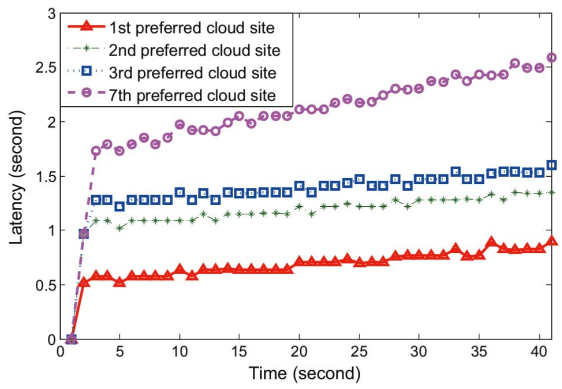


Fig. 9. Streaming delay.

B. Measurement Results

To explore the distribution of the 398 planetlab nodes, we measure the RTT latency between the nodes and the cloud sites, and use the cloud site with the minimal latency to approximate their locations. We deploy 18 cloud sites in different regions from Amazon Cloud and Microsoft Azure, 9 from America area, 3 from Europe area, and 6 from Asia Pacific, respectively. As `ICMP` is blocked by the instances from Microsoft Azure, we set up `tcptraceroute` on the planetlab node and use `tcpping` to measure the latency results. In Fig. 8, we present the nodes population and the average RTT latency from their top 1 preferred cloud sites. With the latency results, each sourcer can construct a preference list about available cloud sites. In order to evaluate the streaming performance, we design the experiments to measure live streaming delay and lost frame ratio respectively in our prototype planform.

After the setup of VLC, we can send a live streaming of a screen timer video[6] from the planetlab node to the cloud server. We record the start time of the streaming on the planetlab side, as well as the time we begin to save the live streaming into a file on the cloud server side. Then we can use `ffmpeg` to split both the original video file and the received video frame by frame, and compare them to calculate the delay. As the frame rate of this video is 30fps, the error caused by the video is less than 33 ms. Fig. 9 presents a 40 seconds record about the delay. We

[6][Online]. Availablehttp://www.cs.sfu.ca/%7Ejcliu/TMM/crowdsourcing/videos/timer.mkv

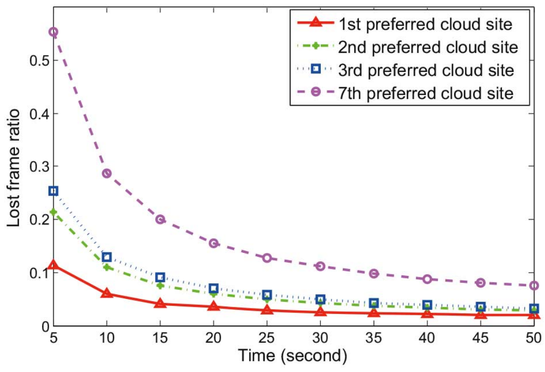


Fig. 10. Lost frame ratio.

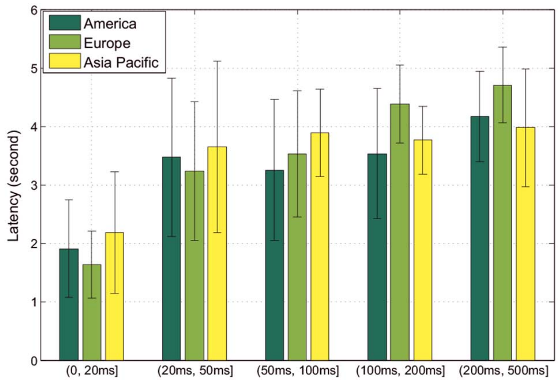


Fig. 11. Different regions.

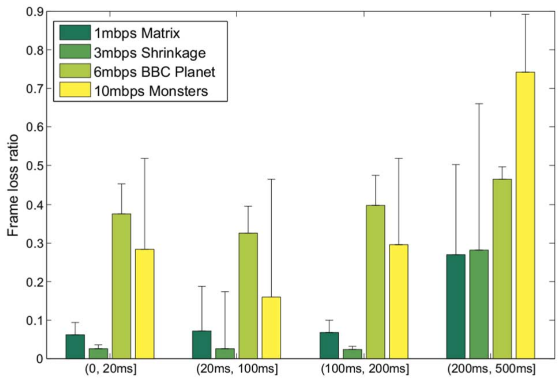


Fig. 12. Different videos.

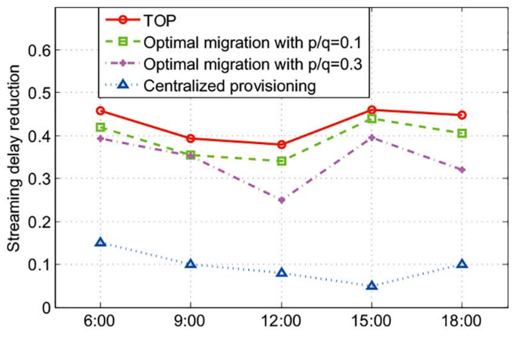


Fig. 13. Streaming delay in different time slots.

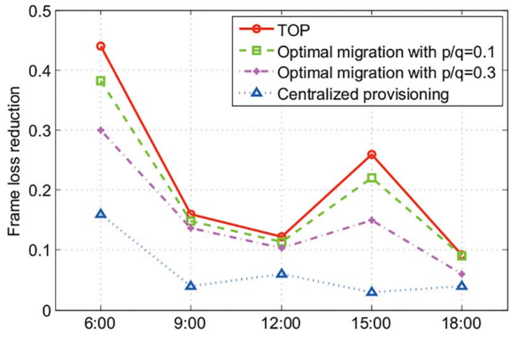


Fig. 14. Lost frame in different time slots.

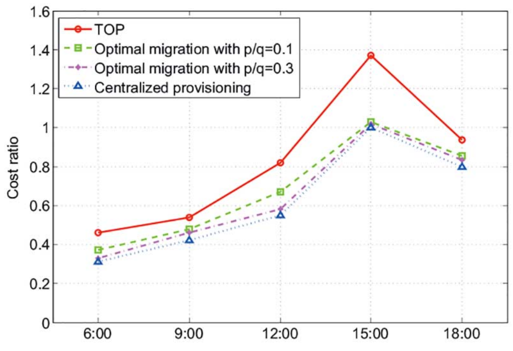


Fig. 15. Cost ratio in different time slots.

can see that the top 1 preference cloud site has a minimal delay, and the delay time will accumulate along with time.

We also use `ffmpeg` to measure the lost frames during the live streaming. These lost frames include both duplicated frames (i.e., because the current frame is not received by the playback deadline, the former frame is duplicated) and dropped frames (i.e., the frame is received but corrupted). In either case, the quality of experience (QoE) of viewer is decreased. Fig. 10 presents a 50 seconds record about the lost frame ratio. Different from the streaming delay, the lost frame ratio will decrease along with time, and the gaps between different cloud sites become minor.

To better understand the relationship between the streaming quality and RTT latency, we explore the cloud sites in different areas and videos with different bit rates. For each cloud site, we divide the planetlab nodes into groups according to the RTT latency. The results on live streaming delay and lost frame ratio are shown in Figs. 11 and 12, respectively. From Fig. 11, we observe all the cloud sites in different regions have a sharp delay increase when RTT latency is larger than 20 ms. Meanwhile, given the different videos, we can observe an obvious lost frame ratio increase when RTT latency is larger than 200 ms in Fig. 12. Generally, we can see the streaming delay increase more than 80% if the latency is above 20 ms. On the other hand, the frame loss ratio is relatively stable when the latency is under 200 ms.

C. Prototype Implementation

We present the implementation results to evaluate our proposed strategy in the prototype system. The planetlab nodes are split into different areas, and the number of planetlab nodes deployed in each area is proportional to the sourcer distribution of the real world trace in Fig. 3. From 9:00AM to 18:00PM,

TABLE IV
CLOUD LEASING STRATEGIES FOR CROWDSOURCED LIVE STREAMING FROM 7 AREAS AT 18:00

	Van (10)	CA (19)	VA (20)	SA (5)	K. and J. (20)	CHN (16)	S. and A. (4)	Cost
TOP	m3 × 3 (Oregon)		m3 × 2 (Virginia)	m1 × 1 (Sao Paulo)	m3 × 2 (Tokyo)	m3 × 1+ m1 × 1 (Singapore)	m1 × 1 (Sydney)	$5.584 per Hour
OM p/q=0.1	m3 × 3 (Oregon)		m3 × 2 + m1 × 1 (Virginia)		m3 × 2 (Tokyo)	m3 × 2 (Singapore)		$5.118 per Hour
OM p/q=0.3	m3 × 5 (Virginia)				m3 × 2 (Tokyo)	m3 × 2 (Singapore)		$4.978 per Hour
CP	m3 × 5 (Virginia)				m3 × 4 (Singapore)			$4.77 per Hour

we implement the different cloud leasing strategies with every 3 hours as an interval. In our proposed `optimal migration` (OM) strategy, we have two scenarios with $p/q = 0.1$, and $p/q = 0.3$. Another two cloud-based strategies are also implemented for comparison. The `top preferred first` (TOP) strategy deploys all the available cloud sites to allocate the service for sourcers in their most preferred cloud site. Meanwhile, the cloud servers are allocated in the regions with the most sourcers in `centralized provisioning` (CP) strategy. We consider a conventional `centralized dedicated server` (CDS) strategy as the benchmark, in which the single server is allocated in the central region to service the global requests. Fig. 13, 14 and 15 present the implementation results of streaming delay, the loss frame ratio and cost ratio, respectively. Comparing with the benchmark strategy, both TOP and our proposed strategy can have 40% streaming delay reduction on average, and our proposed strategy can further cut about 15% provisioning cost than TOP. The loss frame reduction is more unstable in different time slots. At 18:00, the Virginia and Singapore are selected as the central regions in the benchmark strategy with minor loss frame and cost ratio reduction relatively.

Specifically, we further present the implementation results of different regions at 18:00, when most sourcers come from North America and Asia areas. Here, we deploy totally 94 plantlab nodes (i.e. crowdsourcers) distributed in 7 areas all over the world, specifically, 10 nodes in Vancouver area (Van for short), 19 nodes in California area (CA for short), 20 nodes in Virginia area (VA for short), 5 nodes in South America area (SA for short), 20 nodes in Korean and Japan area (K. and J. for short), 16 nodes in China area (CHN for short), and 4 nodes in Singapore and Australia area (S. and A. for short). In Amazon Cloud, EC2 instances are provisioned from 6 different cloud site regions. The implementation details of the cloud leasing strategy are presented in Table IV, and the average frame loss reduction is recorded in Fig. 16 with centralized provisioning as the benchmark. In Table IV, $\mathrm{m3} \times 1 + \mathrm{m1} \times 1$ (Singapore) means one m3.xlarge instance and one m1.large instance are provisioned in Singapore region to serve 16 sourcers. We also calculate the server provisioning cost per hour according to the prices of Amazon EC2. CloudFront is deployed as CDN for the global distribution, and we record the average frame loss ratio from 20 distributed users. Generally the frame loss ratios can be reduced by about 10% for TOP and OM ($p/q = 0.1$) strategies. Especially, for the plantlab nodes in China, the improvement can reach almost 30% with the OM ($p/q = 0.1$) strategy. Comparing with TOP strategy, our proposed solution OM ($p/q = 0.1$) saves 8.34% cost, and improves 9.1% video quality on average. On the other hand, although OM ($p/q = 0.3$) strategy has little performance improvement for Van, CA, VA, and SA areas, it achieves similar improvement for the other three areas and can further reduce the cost by 2.5%.

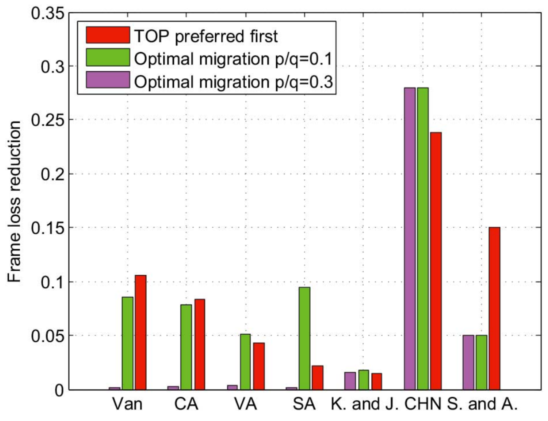


Fig. 16. Implementation results for different regions at 18:00.

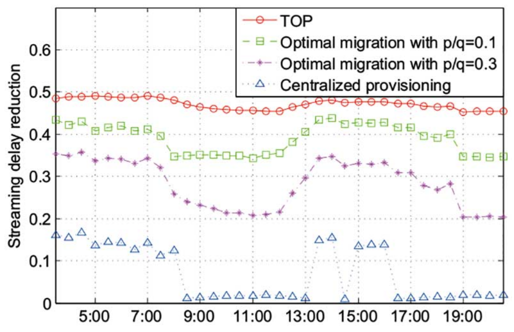


Fig. 17. Reduction of streaming delay.

D. Trace-Driven Simulation Results

To further evaluate the performance of the proposed strategy in larger scale, we simulate the system with the real world trace data from Twitch.tv and the measurement results from the prototype system. The diverse prices of distributed cloud sites are referred to Amazon Cloud and Microsoft Azure Cloud. The price cost should cover the peak user demand, and we will take this cost as the budget constraint in our proposed OM strategy. We also set $p/q = 0.1$ and $p/q = 0.3$. The preference value is inversely proportional to the RTT latency. Another two cloud based strategies are deployed for comparison. All these cloud-based strategies can scale their provisioning capacity adaptively to the user demand.

Fig. 17 shows the streaming delay reduction of the four cloud-based strategies comparing with the benchmark CDS strategy. Generally, TOP and OM strategies, which deploy the

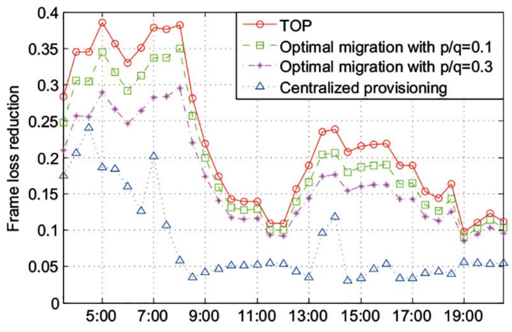


Fig. 18. Reduction of frame loss.

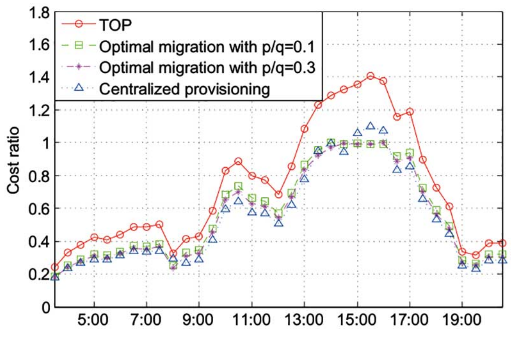


Fig. 19. Reduction of provisioning cost.

geo-distributed cloud service, can reduce almost 50% streaming delay of the benchmark strategy. The CP strategy can have an improvement only when most of viewers concentrate on several sourcers from the same region (e.g. 3:00AM-8:00AM in Asia and 13:00PM-16:00PM in Europe). Different from the streaming delay reduction, the frame loss reduction is more dynamic with time variations in Fig. 18. Before 8:00 AM, most of popular sourcers are from Europe and Asia, the CDS strategy would suffer from the long transmission, despite the total number of streams is not large, and there is still extra available bandwidth capacity for the rented server. After 9:00AM, sourcers from north America attract more viewer demand. Then dedicated server can provide an acceptable service with less frame loss ratio. In Fig. 19, we present the cost ratio between the four cloud-based strategies and the benchmark strategy. As the server instances are allocated in the distributed cloud sites with diverse prices, the TOP strategy can lead to a higher cost when the peak demand comes. Because of the budget constraint, the provisioning cost in our proposed strategy is limited under the cost of the benchmark. Yet, comparing with the TOP strategy, the gap of streaming delay and frame loss ratio can still be kept within 5%, and almost 30% of the provisioning cost is saved through the service migration during peak demand. When p/q is improved from 0.1 to 0.3 we can observe a general increase of the streaming delay for about 10% on average in Fig. 17. The gap is obvious around 12:00PM, when most streams and viewers come from US regions. In Fig. 18, the gap of frame loss is relatively small, and can reach the peak for about 5% during 5:00AM to 8:00AM, when most streams and viewers come from Asia regions. Comparing with OM $p/q = 0.1$, OM $p/q = 0.3$ can generally save about 2% cost, expect for the peak demand around 15:00PM in Fig. 18.

VII. Conclusion and Future Work

In this paper, we explored the emerging live streaming systems for crowdsourced multimedia big data, in which both the number and distribution of the crowdsourcers can be highly dynamic. It further motivated the design of cloud leasing strategy to optimize the cloud site allocation for geo-distributed live crowdsourcers. A prototype of crowdsourced live streaming platform was built with Amazon Cloud/Microsoft Azure and Planetlab nodes. The performance of the proposed strategy was evaluated through extensive experiments.

Our work is an initial study, and there are still many open issues to be further explored. We plan to continue enhancing our design by conducting more evaluations on our prototype with larger scale experiments. Our ongoing work includes tailoring our method for some specific crowdsourced live streaming applications, such as synchronizing multiple collaborative crowdsourced live videos for 3D immersive environment reconstruction or real-time interaction. We are also interested in extending our current deployment strategy to a more general scenario, in which the distributed server instances can cooperate with CDNs for a larger service coverage with a lower cost. In addition, we believe that the dynamic geo-distributed crowdsourcers are predictable, in which there are two major types of live sources, namely, scheduled sources and non-scheduled sources. The scheduled sources mean the crowdsourcers follow some social event in a fixed location during a certain time, such as a presidential election, or a football match. In this case, the number of sourcers is easy to predict, as it usually can be inferred from the number of audience. As to the non-scheduled sources, the crowdsourcers can start their live streaming arbitrarily. While, these time-varying live sources usually tend to adjust their schedule according to the dynamic viewers demand, since they are motivated to get more subscribers as a reward. Especially, some popular crowdsourcers may start to broadcast in a fixed time every day which is convenient for the native language speaking viewers, or choose a period when a peak number of viewers can be achieved. This behavior of crowdsourcers is evident in some modern crowdsourced live streaming platform, such as Twitch.tv. Our solution could be enhanced with crowdsourcer prediction through user behavior analysis from real-world measurement results.

References

[1] J. Liu, S. G. Rao, B. Li, and H. Zhang, "Opportunities and challenges of peer-to-peer internet video broadcast," *Proc. IEEE*, vol. 96, no. 1, pp. 11–24, Jan. 2008.

[2] B. Li, Z. Wang, J. Liu, and W. Zhu, "Two decades of internet video streaming: A retrospective view, ACM Transactions on Multimedia Computing, Communications and Applications," *Special 20th Aniversary ACM SIGMM Multimedia*, vol. 9, no. 1, pp. 1–20, Oct. 2013.

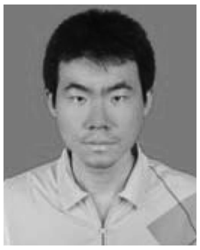
[3] H. Ma, D. Zhao, and P. Yuan, "Opportunities in mobile crowd sensing," *IEEE Commun. Mag.*, vol. 52, no. 8, pp. 29–35, Aug. 2014.

[4] C. Wu, Z. Yang, and Y. Liu, "Smartphones based crowdsourcing for indoor localization," *IEEE Trans. Mobile Comput.*, vol. 14, no. 2, pp. 444–457, Feb. 2015.

[5] Z. Ou *et al.*, "Utilize signal traces from others? A crowdsourcing perspective of energy saving in cellular data communication," *IEEE Trans. Mobile Comput.*, vol. 14, no. 1, pp. 194–207, Jan. 2015.

[6] J.-I. Biel and D. Gatica-Perez, "Mining crowdsourced first impressions in online social video," *IEEE Trans. Multimedia*, vol. 16, no. 7, pp. 2062–2074, Nov. 2014.

[7] P. Simoens *et al.*, "Scalable crowd-sourcing of video from mobile devices," in *Proc. ACM MobiSys*, 2013, pp. 139–152.
[8] F. Wang, J. Liu, and Y. Xiong, "Stable peers: Existence, importance, and application in peer-to-peer live video streaming," in *Proc. IEEE INFOCOM*, Apr. 2008, pp. 2038–2046.
[9] Z. Zhuang and C. Guo, "Optimizing CDN infrastructure for live streaming with constrained server chaining," in *Proc. IEEE Parallel Distrib. Process. Appl.*, May 2011, pp. 183–188.
[10] Y. Feng, B. Li, and B. Li, "Bargaining towards maximized resource utilization in video streaming datacenters," in *Proc. IEEE INFOCOM*, Mar. 2012, pp. 1134–1142.
[11] F. Wang, J. Liu, and M. Chen, "CALMS: Migration towards cloud-assisted live media streaming," in *Proc. IEEE INFOCOM*, to be published.
[12] H. Yin *et al.*, "Design and deployment of a hybrid CDN-P2P system for live video streaming: Experiences with LiveSky," in *Proc. ACM Multimedia*, 2009, pp. 25–34.
[13] Z. Wang, L. Sun, C. Wu, W. Zhu, and S. Yang, "Joint online transcoding and geo-distributed delivery for dynamic adaptive streaming," in *Proc. IEEE INFOCOM*, Apr.–May 2014, pp. 91–99.
[14] Y. Wu *et al.*, "Scaling social media applications into geo-distributed clouds," in *Proc. IEEE INFOCOM*, Mar. 2012, pp. 684–692.
[15] V. K. Adhikari *et al.*, "Unreeling Netflix: Understanding and improving multi-CDN movie delivery," in *Proc. IEEE INFOCOM*, Mar. 2012, pp. 1620–1628.
[16] C. Liu, I. Bouazizi, and M. Gabbouj, "Rate adaptation for adaptive HTTP streaming," in *Proc. ACM Multimedia Syst.*, 2011, pp. 169–174.
[17] V. Aggarwal, V. Gopalakrishnan, R. Jana, K. K. Ramakrishnan, and V. A. Vaishampayan, "Optimizing cloud resources for delivering IPTV services through virtualization," *IEEE Trans. Multimedia*, vol. 15, no. 4, pp. 789–801, Jun. 2013.
[18] D. Niu, Z. Liu, B. Li, and S. Zhao, "Demand forecast and performance prediction in peer-assisted on-demand streaming systems," in *Proc. IEEE INFOCOM Mini-Conf.*, Apr. 2011, pp. 421–425.
[19] H. N. Gabow and E. W. Myers, "Finding all spanning trees of directed and undirected graphs," *SIAM J. Comput.*, vol. 7, no. 3, pp. 280–287, 1978.
[20] S. Kapoor and H. Ramesh, "An algorithm for enumerating all spanning trees of a directed graph," *Algorithmica*, vol. 27, no. 2, pp. 120–130, Jun. 2000.

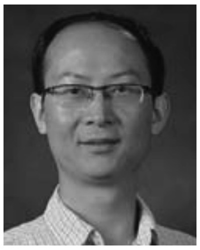


Fei Chen (S'13–M'14) received the M.S. degree in electronics engineering and computer science from Northeastern University, Shenyang, China, in 2009, and the Ph.D. degree in computing science from Simon Fraser University, Burnaby, BC, Canada, in 2014.

He is currently an Assistant Professor with the School of Digital Media, Jiangnan University, Wuxi, China. His research interests include cloud computing, peer-to-peer networks, crowd-sensing systems, and multimedia communications.

Cong Zhang (S'14) received the M.S. degree in information engineering from Zhengzhou University, Zhengzhou, China, in 2012, and is currently working toward the Ph.D. degree in computing science at Simon Fraser University, Burnaby, BC, Canada.

He is currently working with the Network Modeling Research Group, Simon Fraser University, Burnaby, BC, Canada. His research interests include multimedia communications, cloud computing, and crowdsourcing system.



Feng Wang (S'07–M'13) received the B.Sc. and M.S. degree in computer science and technology from Tsinghua University, Beijing, China, in 2002 and 2005, respectively, and the Ph.D. degree in computing science from Simon Fraser University, Burnaby, BC, Canada, in 2012.

He is currently an Assistant Professor with the Department of Computer and Information Science, University of Mississippi, University, MS, USA. His research interests include cloud computing, peer-to-peer networks, socialized content sharing, wireless mesh/sensor networks, cyber-physical systems, and big data.

Dr. Wang served as Program Vice Chair for the International Conference on Internet of Vehicles 2014 and TPC Co-Chair at the IEEE International Conference on Communications in China 2014 for the Symposium on Wireless Networking and Multimedia. He also serves as TPC Member for various international conferences such as IEEE/ACM IWQoS, ACM Multimedia, IEEE ICC, IEEE GLOBECOM, IEEE CloudCom, and IEEE ICME. He was a recipient of the Chinese Government Scholarship for Outstanding Self-financed Students Studying Abroad in 2009 and the IEEE ICME Quality Reviewer Award in 2011.

Jiangchuan Liu (S'01–M'03–SM'08) received the B.Eng. degree (*cum laude*) from Tsinghua University, Beijing, China, in 1999, and the Ph.D. degree from The Hong Kong University of Science and Technology, Hong Kong, China, in 2003, both in computer science.

From 2003 to 2004, he was an Assistant Professor with The Chinese University of Hong Kong, Hong Kong, China. He is currently a Full Professor with the School of Computing Science, Simon Fraser University, Victoria, BC, Canada. He is an EMC Endowed Visiting Chair Professor of Tsinghua University, Beijing, China (2013–2016). His research interests include multimedia systems and networks, cloud computing, social networking, online gaming, big data computing, wireless sensor networks, and peer-to-peer and overlay networks.

Dr. Liu is an NSERC E.W.R. Steacie Memorial Fellow. He has served on the editorial boards of the IEEE TRANSACTIONS ON BIG DATA, the IEEE TRANSACTIONS ON MULTIMEDIA, the *IEEE Communications Surveys and Tutorials*, IEEE ACCESS, the IEEE INTERNET OF THINGS JOURNAL, *Elsevier Computer Communications*, and *Wiley Wireless Communications and Mobile Computing*. He was a co-recipient of the inaugural Test of Time Paper Award of IEEE INFOCOM (2015), ACM TOMCCAP Nicolas D. Georganas Best Paper Award (2013), ACM Multimedia Best Paper Award (2012), IEEE Globecom Best Paper Award (2011), and the IEEE Communications Society Best Paper Award on Multimedia Communications (2009).

Xiaofeng Wang received the Ph.D. degree in computer science from the Harbin Institute of Technology, Harbin, China, in 2007.

He is currently an Associate Professor with the School of Internet of Things Engineering, Jiangnan University, Wuxi, China. His main research interests include network and information security and network simulations.

Yuan Liu received the B.S. degree in electrical engineering from Fudan University, Shanghai, China, in 1987, and the M.S. degree in control science and engineering from Jiangnan University, Wuxi, China, in 1998.

He is currently a Full Professor with the School of Digital Media, Jiangnan University, Wuxi, China. His research interests include multimedia communications, network protocols, and information security.