Background Traffic Load Aware Video Class-lecture Client Admission in a Bandwidth Constrained Campus Network

Siti Aisyah binti Haji Jalil[a], Amirah Ruyaieda binti Haji Abdul Majid[a], Mohammad Ramzi bin Salleh[a], Fatin Hamadah Rahman[a], Mohammad Rakib Uddin[a], S.H. Shah Newaz[a, b], Gyu Myoung Lee[c]

[a] Universiti Teknologi Brunei, Jalan Tungku Link, Gadong, BE1410, Brunei Darussalam.
[b]KAIST Institute for Information Technology Convergence, 291 Daehak-ro, Yuseong-gu, Daejeon 34141, South Korea.
[c]Faculty of Engineering and Technology, Liverpool John Moores University, Liverpool, United Kingdom.

bcns0314.021@student.utb.edu.bn,bcns0314.014@student.utb.edu.bn,bcns0314.010@student.utb.edu.bn,P20171005@student.utb.edu.bn,rakib.uddin@utb.edu.bn,shah.newaz@utb.edu.bn,G.M.Lee@ljmu.ac.uk

Abstract. Video class-lecture streaming is regarded as a popular means in improving quality of teaching and learning in schools and universities. Several research findings reveal that, recorded lecture videos (streamed over the Internet) are a useful supplement to non-classroom learning. Despite knowing this importance, some schools or universities are reluctant to use video lecture streaming service in their campus network, thinking video streaming service would impose additional traffic load in their network. In fact, in a bandwidth constrained campus network, other regular traffic flows may experience lower throughput, packet drop and delay due to presence of class lecture video streaming traffic, resulting in deteriorating Quality of Experience (QoE) of campus users. In this paper, we propose video streaming service model for the bandwidth constrained campus networks. We refer to our solution as Class Lecture on Demand (CLD) service that can be easily adopted in a campus. CLD defines the policies for admitting number of clients that request for video streaming service taking into account peak hour and off-peak hour background traffic load. This paper provides a detailed procedures, showing how a network administrator in a bandwidth constrained campus network can measure the maximum number class lecture streaming requests that a video streaming server should accommodated at different part of a day without affecting other traffic flows. Additionally, we provide an insightful discussion (policies) in order to make video lecture streaming in a bandwidth constrained campus network easily adopted.

Keywords: Captured class-lecture, video streaming policy, QoE, background traffic, campus network.

1 Introduction

Class-lecture video streaming could effect attendance and engagement in a class. Further, while a lecturer delivers a lecture, the video capturing process may restrict his/her spontaneous lecture-delivery style [2]. Despite these downsides, class-lecture video streaming is found to be an effective mean to improve learning outcomes [3]. Technological advancement for multimedia content generation, processing and storage is contributing rapid growth of video lecture service. Aside from this, we believe, one important factor that is playing important role to facilitate this move is availability of hand-held devices with low cost and high processing capability.

Authors in [2] highlight several important aspects that may impede adopting class-lecture video streaming. In our opinion, due to limited network resources some schools and universities may reluctant as well to introduce this service to their students. The main objective of this paper is to propose a class-lecture video steaming service model over a bandwidth constrained campus networks. We propose this model taking into account: *(i)* university campus regular traffic load (without class-lecture streaming) throughout a day, *(ii)* number of students (clients) interested in the video streaming service, and *(iii)* Quality of Experience (QoE) of clients. We refer to our solution as Class Lecture on Demand (CLD) service. In this paper, the prime objective of CLD is to introduce a set of policies in order to facilitate video class-lecture streaming in a bandwidth constrained campus network. Following the policies, we provide based on our study, one can find the maximum number of video class-lecture streaming clients that can be accommodated with providing satisfactory QoE during peak and off-peak hours of a day (without deteriorating the existing QoE of background traffic flows).

The remainder of this paper is organized as follows. Section II discusses relevant research. Section III presents details of video lecture streaming performance study in a bandwidth constrained campus scenario. Section IV provides recommendations for further improvement of video streaming service in a bandwidth constrained campus network. Section V concludes this paper.

2 Related Work

2.1 Research on QoE Evaluation

Research activities on the QoE evaluation of video streaming has been increasing in the recent years. To date, there are many research efforts to understand the influence of packet delay, packet drop and jitter in video streaming service on QoE of end users. For instance, Bhamidipati and Kilari [1] had made a survey on 41 users to analyse the quality of the video shown to them with varying delays. Based on their research, they concluded that the delay variation contributes tremendously in degrading users' QoE (a small delay variation can have catastrophic influence on video quality). A similar study was conducted in [7] in an attempt to reveal how the network QoS can influence the QoE of video streaming over HTTP. From their findings, they concluded that network throughput may drop due to packet loss and delay.

Zhengyou et.al. in [8] used a QoS/QoE mapping assessment model for the relationship between QoS and QoE. They conducted an experiment using NS2 network simulator and *myEvalvid* in order to meet their research objectives. Their findings can be used to predict QoE based on QoS parameters. Authors in [4] provided as well a correlation model for QoE evaluation in IPTV.

In [5], authors observed how packet loss may influence video stream transmission. They emphasized that a larger packet size will lead to better quality of received video than that of smaller packets carrying video frames (larger the packet size, the better the quality of video received). The authors conclude that, if a video is segmented into smaller packets, it is possible that the video may suffer from losses of I-frames. Note that, I-frames is increasingly important to decode the frame, and hence loss of I-frames will lead to affecting the entire groups of frames.

There are two popularly used methods to estimate the QoE: objective assessment and subjective assessment. In objective assessment approach, mathematical modeling is required in order to infer human perception relating to a video quality. As this approach relies solely mathematical formulation, this approach is cheap and quick. On the other hand, in subjective assessment method, a subject is shown a video and then, the opinion of the subject relating to the perception on quality of the video is recorded. That is, subjective method is a approach for measuring subject's perceived opinion on the quality of a video—it is the analysis of the subjects' Mean Opinion Score (MOS). To date, there are several objective assessment methods have been introduced already. In fact, one objective assessment method (mathematical model) can be regarded as a reliable model if the objective assessment results are close to a subjective assessment result based on the same video. Interestingly, it has been noticed that objective assessment results fail to correlate properly with the reality most of the time. Considering this fact, many researchers prefer subjective assessment for inferring QoE of a video over the objective assessment method.

Table 1: MOS rating for subjective quality measurements.

MOS	**Quality**	**Perception**
5	Excellent	Imperceptible
4	Good	Perceptible
3	Fair	Slightly Annoying
2	Bad	Annoying
1	Poor	Very annoying

2.2 Importance of Video Streaming

Video streaming is an attractive solution due to two important reasons. First, a client can start watching video immediately after selecting play option while video is being streamed instead of waiting for the entire video to be downloaded. In case when the video file size is big, assume a two-hour lecture video, it would take intolerably long time to download the entire file over a low speed Internet connection [6]. Second, video streaming would not consume much memory space in a user device. In order facilitate video streaming over Internet, a video streaming server first needs to encode the video file to reduce file size. The growing importance of video streaming service propelled significant research on designing video delivery protocols (e.g. real-time transport protocol, real-time transport control protocol) over Internet and video encoding mechanism (e.g. H.264) over the last couple of decades.

3 Proposed Class Lecture on Demand (CLD) Service

Our proposed approach composed of three steps: *(i)* understanding background traffic profile, *(ii)* evaluating MOS under peak and off-peak hours background traffic load profile for different number of video class-lecture clients, and *(iii)* providing QoE aware client admission policies. In order to test QoE of videos in a bandwidth constrained campus scenario, the overall experimentation procedures are stated in Figure 1.

3.1 Understanding Background Traffic Profile

Campus network will be serving different kinds of traffic along with the video class-lecture clients. Therefore, we need to understand the behavior of traffic that the campus network serves (excluding video class-lecture traffic). We refer to this kind of traffic as background traffic in this paper. We produce a background traffic graph to investigate the traffic pattern in Figure 2. Let $S = \{s_1, s_2, \ldots, s_N\}$ be the set of traffic load sample points from the traffic load profile depicted in Figure 2.

3.2 Mean Opinion Score (MOS) Analysis

Based on the traffic profile depicted in Figure 2, we are interested to find the maximum number of class-lecture video clients can be admitted at a given time (t). Let $M^{(t)}$ denote the number of class-lecture video clients and $B^{(t)}$ represents bandwidth consumed due to background traffic at time t. Assume, γ is the average bandwidth consumption of a class-lecture video at a certain compression rate (α) and BW_{max} is the maximum throughput of the campus network can offer. Then, the following condition should hold in order not to deteriorate QoE of the background flows.

$$\gamma M^{(t)} + B^{(t)} \leq BW_{\max}. \tag{1}$$

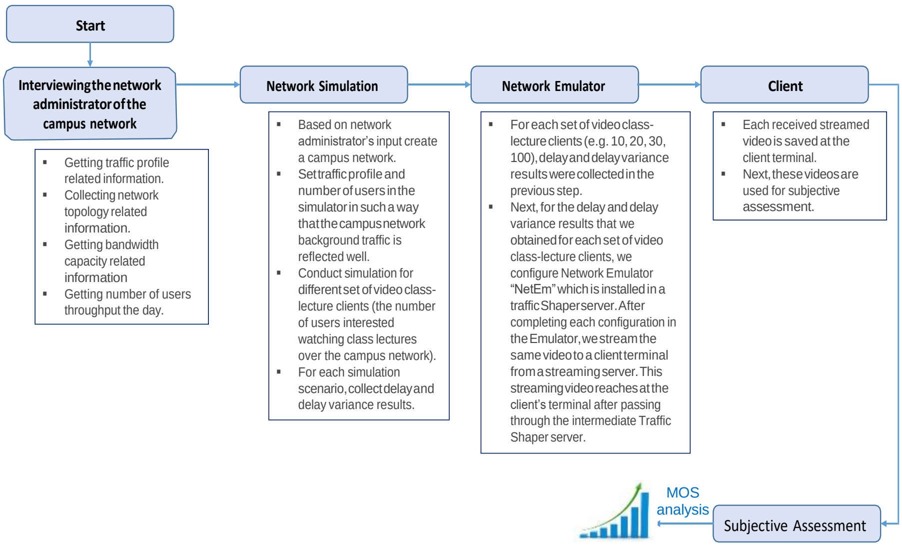

Fig. 1: Overall experimental procedures.

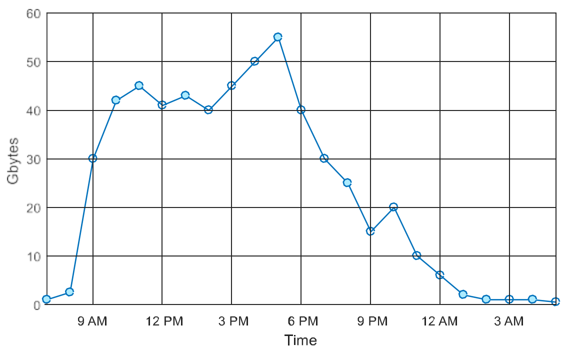

Fig. 2: 24 hours traffic profile in a campus.

At this stage of our experiment, for different $B^{(t)}$ values, we check the MOS of different $M^{(t)}$ values for a certain compression rate of a video. Note that, in our experiment, we will be choosing two different kind of videos: fast video (consider the case in which lecturer has relatively high movement during class lecture period) and slow video (consider the case in which the lecturer has a few movement while delivering lecture at a class).

In our study, following the traffic profile illustrated in Figure 2, we select upper boundary ($B^{upper} = max\{S\}$) and lower boundary ($B^{lower} = min\{S\}$) of the background traffic load. We consider that these two boundaries represent maximum and minimum traffic load during peak and off-peak hours of a campus traffic demand, respectively. We are interested to find at these two boundaries

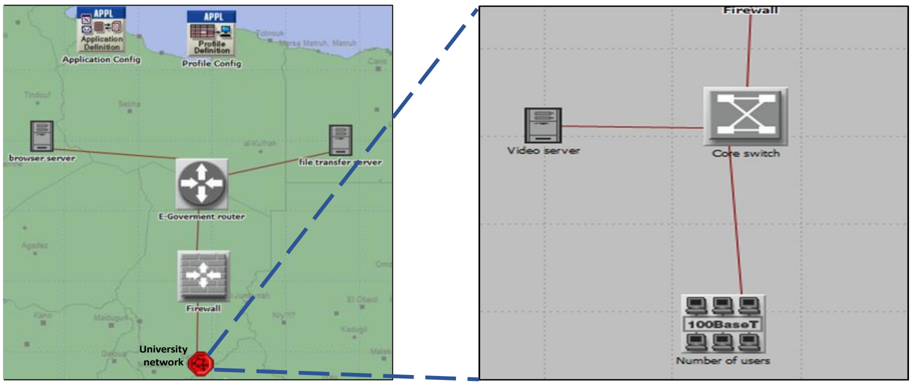

Fig. 3: Understanding campus network traffic performance during peak and off-peak hours using OPNET.

the maximum number of class-lecture video clients (M) can be accommodated. In order to do so, in OPNET simulator, we created background traffic for both B^{upper} and B^{lower}. We assume the background traffic is mainly FTP and HTTP traffic.

We roughly estimated that 600 (B^{upper}) and 50 (B^{lower}) FTP and HTTP browsing background traffic flows in our simulation setup (in OPNET) would represent peak hours and off-peak hours traffic load presented in Figure 2, respectively. We have several simulation scenarios in our experiment. For each scenario we configure in OPNET simulator, we collect delay and delay variance results. Here, below we explain the simulation setup and procedures:

Step 1: For the slow video, we set B^{upper} background traffic and we create six simulation scenarios for different values of M (6, 36, 54, 66, 69 and 72).
Step 2: We follow the same procedures stated in Step 1 for the fast video.
Step 3: For each slow video, we set B^{lower} background traffic and we create six simulation scenarios for different values of M (6, 36, 54, 66, 69 and 72).
Step 4: We follow the same procedures stated in Step 3 for each fast video.

Results (delay and delay variance results) from aforementioned simulation scenarios are recorded and tabulated in Table 2. From this table, we can infer that, for example, in case of slow video, during peak hours ($B^{upper} = 600$ FTP+HTTP traffic), if there are six video class-lecture clients (i.e. $M = 6$), the class-lecture videos would experience 1.6068 ms delay and 0.000008095 ms delay variance. Similarly, during the peak hours, if $M = 72$, video class-lecture clients would experience 924.05 ms delay and 135.1 ms delay variance. Upon completion of the network simulation, NetEm emulator is used in order to see how each of the delay and delay variance pairs presented in Table 2 affects a video. The setup is illustrated in Figure 4.

Note that, we have 24 pairs of delay and delay variance results, as we can notice from Table 2. The NetEm emulator is configured to see the impact of each

Table 2: Delay and delay variance results for different M values during peak and off-peak hours of a day in a bandwidth constrained campus network.

Video Type	Scenario	Number of Users: ftp + browsing	Number of Users: video	Delay (ms)	Delay Variance (ms)
Slow Video (News)	Peak Hours	600	6	1.6068	0.000008095
			36	1.9645	0.00007371
			54	2.84	0.00000006285
			66	4.1855	0.0003569
			69	4.524268	0.0011055
			72	924.05	135.1
	Off-Peak Hours	50	6	1.5705	0.000000002275
			36	1.8315	0.00001073
			54	2.5785	0.00017055
			66	5.0495	0.00030295
			69	6.09149	0.002585
			72	1693.8175	467.0275
Fast Video (Pamphlet Man)	Peak Hours	600	6	1.6068	0.000008095
			36	1.9645	0.00007371
			54	2.84	0.00000006285
			66	4.1855	0.0003569
			69	4.524268	0.0011055
			72	924.05	135.1
	Off-Peak Hours	50	6	1.5705	0.000000002275
			36	1.8315	0.00001073
			54	2.5785	0.00017055
			66	5.0495	0.00030295
			69	6.09149	0.002585
			72	1693.8175	467.0275

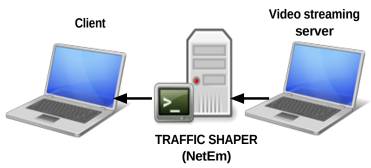

Fig. 4: Network emulator test-bed setup.

pair of delay and delay variance (the procedure is repeated for all the cases in Table 2 for both slow and fast videos). For each setup, video from the streaming server is streamed and saved at the client side after the video is shaped with the traffic shaper (see Figure 4). Therefore, finally, we have 24 videos saved in client side, each of which represents the effect on video quality for each pair of delay and delay variance results stated in Table 2. The screenshots of some of the videos that are saved in client side are depicted in Figure 5 and 6 for both peak hours (B^{upper}) and off-peak hours traffic load (B^{lower}) case. Looking at these figures, we can easily perceive that with the increment of video class-lecture clients (M) the video quality deteriorate (when M = 72 the videos are almost unrecognizable).

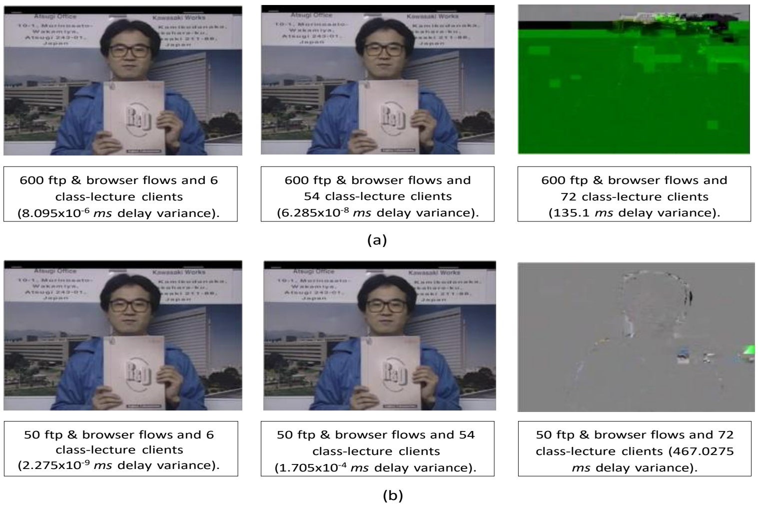

Fig. 5: Fast video quality for peak hours and off-peak hours background traffic under different *M* values: (a) peak hours scenario; and (b) off-peak hours scenario.

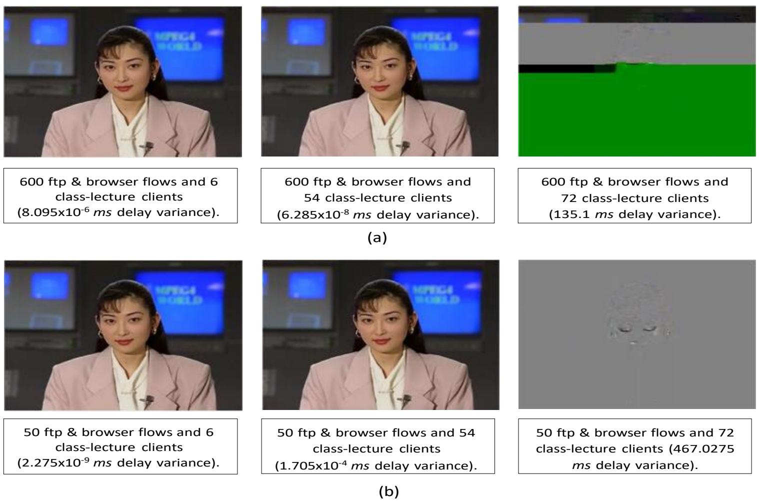

Fig. 6: Slow video quality for peak hours and off-peak hours background traffic under different *M* values: (a) peak hours scenario; (b) off-peak hours scenario.

In this paper, we use subjective assessment as it relates to our experiment. To get MOS, a subjective assessment with 20 human subjects are conducted. Out of 20 human subjects, there are 10 males and 10 females with age group of 20 to 33 years old. Each user (subject) is shown 24 video sequences of which 12 of them are slow movement videos called *News*, and the remaining 12 videos are fast movement videos called *Pamphlet Man*. For displaying the streaming video,

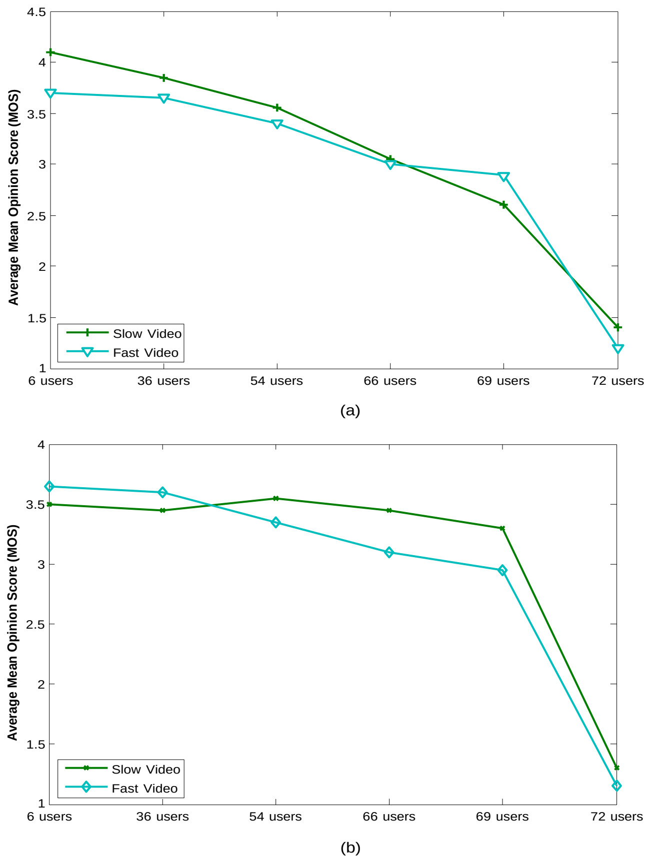

Fig. 7: Aggregated average MOS of videos during peak hours and off-peak hours under different value of M: (a) peak hours MOS (scenario considers B^{upper}); (b) off-peak hours MOS (scenario considers B^{lower}).

each user is allocated a laptop and the content is viewed only by a single user (discussion among the subjects is not allowed during this assessment).

Once the subjects watch all the videos without knowing the delay and delay variance have been added, they rate the videos based on the video quality they perceived. The video files are given different names, such as *Video1* to *Video24*. We do not want the subjects to have any clue about the delay and delay variance each of the videos experienced. In order to accomplish this, the videos are not played in descending or ascending order of delay and delay variance. After completing watching each of the videos, the subject rate his/her perception on the quality of the video (subject selects one of the five ratings on a continuous scale from 1 to 5, as shown in Table 1).

All feedbacks were recorded and gathered to calculate the average MOS per scenario. In Figure 7, the aggregated average MOS for both slow and fast videos during peak hours (600 FTP and HTTP browser) and off-peak hours (50 FTP and HTTP browser) are plotted together as to make comparison of the average MOS. The graph shows that the average MOS decreases as M increases.

The lowest average MOS rating noticed in case of peak hours (see Figure 7 (a)). It shows that when $M = 72$ the average MOS rating of 1.2, indicating poor video quality. Figure 7 (a) shows when $M > 66$ during peak hours viewers' rating for fast video is less than 3. This implies that perception based on video quality is annoying or very annoying. However, in case of off-peak hours (see Figure 7 (b)), when $M > 69$, viewers have the same opinion. Therefore, we surmise, obviously, we can accommodate more video class-lecture clients (M) during off-peak hours than the peak hours.

By comparing the peak and off-peak hours MOS results, the QoE of both slow and fast video abruptly decreases as the delay variance and delay increase (due to increment of the value of M). Both peak hours and off-peak hours ratings are approximately similar for both slow and fast videos. Despite that, most of the fast videos show a lower average MOS compared to slow videos. A fast video is more affected with delay variance because it has a more movement compare to a slow video.

3.3 QoE Aware Video Class-lecture Admission Policies

It has been noticed that with the increased number of M (video class-lecture clients), the video quality deteriorates as noticed in Figure 5, 6 and 7. When video streaming service is in operation, the value of M should be set carefully during peaks and off-peak hours of a day. For instance, if the steaming server wants to meet MOS greater than or equal 3, the number of CLD clients should not be more than 66 and 69 during peak hours and off-peak hours, respectively, as observed from Figure 7. Overall, taking the background traffic load into account, the streaming server should be configured in such a way that MOS requirement threshold does not get violated for the video class-lecture clients.

Our study also reveals that the lectures' movement behavior could influence MOS. A lecturer with high movement relatively during the class lecture capturing would be more affected with packet delay variance. In turn, this would result in reducing MOS compared to the case when the lecturer has very slow movement during capturing a lecture (slow video).

4 Recommendations

Based on our study, we have the following suggestions that would improve class-lecture video streaming performance at a bandwidth constrained campus network.

- As an alternative to video streaming in a bandwidth-constrained campus during peak hours, students can be encouraged to download the class lectures during off-peak hours. It would be more convenient if one student downloads and share them with the whole class.

- Video segmentation is a popular approach [9]. The video can be segmented based on some criteria (e.g. topic, class intervals, chapter). Using this approach, instead of downloading the entire class lecture, a student may download the portion that the student wants to watch only, thereby reducing bandwidth consumption and streaming server load.
- Dynamic video quality selection considering the traffic load at a campus at a given time would be useful similar to different existing video streaming services (e.g. YouTube).
- In case when a particular video is highly requested from the students, multicasting mechanism can be applied [11, 12] to reduce bandwidth wastage.
- If many students are interested on a particular video lecture at a given time, the video scheduler can set higher resolution of the video for that class lecture. This will improve the MOS for that video lecture and in return contribute in increasing overall users' satisfaction (QoE).
- It is recommended for the campus network administrator to increase the number of servers and place them at strategic locations in order to reduce network bottleneck points. For example, one way to reduce the load from the centralized server is to place the streaming server close to a dormitory if many students are residing there.
- Peer-to-peer video streaming is a popular mean to reduce load from the streaming servers of video service providers [10]. Aside from the campus owned servers, devices of students—if they are interested—can be used for class lecture storage and streaming purposes.
- Lecturers need to put effort in order to deliver lectures efficiently (make the class-lecture videos concise and effective).
- Lecture capturing process needs to be efficient [2]. Additionally, during post-processing of a captured class-lecture video, no class activity periods can be removed (if there is any) in order to reduce video size of the lecture.

5 Conclusion

In this paper, we proposed a background traffic load aware class-lecture video streaming solution for a bandwidth constrained campus network. Aside from this, for such network, we provided several recommendations to make class-lecture video streaming as a feasible approach. In order to infer QoE performance of class-lecture clients when a bandwidth constrained campus adopts CLD service, we provided a detailed experimental procedures in this paper. In the future research, we aim at incorporating: (i) a QoE and background traffic load aware optimal video quality finding mechanism and (ii) a knowledge (class lecture prerequisites) dependency based video lecture tagging solution.

Acknowledgment

This work was supported by grant No. UTB/GSR/1/2017 (9) from the internal project grant of Universiti Teknologi Brunei (UTB), Brunei Darussalam.

Bibliography

1. Bhamidipati, V. & Kilari, S.: Effect of Delay/Delay Variable on QoE in Video Streaming. M.S. thesis, School of Computing at Blekinge Institute of Technology, Karlskrona, Sweden, May (2010).
2. O'Callaghan, F. V., Neumann, D. L., Jones, L., & Creed, P. A.: The use of lecture recordings in higher education: A review of institutional, student, and lecturer issues. Education and Information Technologies, pp. 1–17 (2015).
3. Hecht, J. B. & Klass, P. H.: The Evolution of Qualitative and Quantitative Research Classes when Delivered via Distance Education. Paper presented at the Annual Meeting of the American Educational Research Association, Ontario, Canada, (ERIC Document Reproduction Service No. ED 430 480).
4. H. J. Kim, S. G. Choi: A study on a QoS/QoE correlation model for QoE evaluation on IPTV service. In Proc. 12th Int. Conf. Adv. Commun. Technol., vol. 2, pp. 1377-1382 (2010).
5. J. S. Mwela & O. E. Adebomi: Impact of packet losses on the quality of video streaming. M. Sc. Thesis School of Sience in Electrical Engineering School of Computing at Blekinge Institute of Technology, Karlskrona, Sweden (2010).
6. McCrohon, M., Lo, V., Dang, J., Johnston, C.: Video Streaming of Lectures Via the Internet An Experience. In: ASCILITE 2001 - The 18th Annual Conference of the Australasian Society for Computers in Learning in Tertiary Education, Melbourne, pp. 397–405 (2001).
7. R. K. P. Mok, E. W. W. Chan and R. K. C. Chang,: Measuring the quality of experience of HTTP video streaming, in 12th IFIP/IEEE International Symposium on Integrated Network Management (IM 2011) and Workshops, Dublin, pp. 485-492 (2011).
8. Z. Wang, L. Li, W. Wang, Z. Wan, Y. Fang and C. Cai: A study on QoS/QoE correlation model in wireless-network. S Proc. Asia–Pacific Signal Inf. Process. Assoc. Annu. Summit Conf. (APSIPA), pp. 1-6 (2014).
9. Shao-Yi Chien, Yu-Wen Huang, Bing-Yu Hsieh, Shyh-Yih Ma & Liang-Gee Chen: Fast video segmentation algorithm with shadow cancellation, global motion compensation, and adaptive threshold techniques. in IEEE Transactions on Multimedia, vol. 6, no. 5, pp. 732-748, Oct (2004).
10. P. Dhungel, X. Hei, K. W. Ross, & N. Saxena,: The pollution attack in P2P live video streaming: measurement results and defenses. P2P-TV '07 Proceedings of the 2007 workshop on Peer-to-peer streaming and IP-TV, pp. 323-328 (2007).
11. S.H. S. Newaz, Y. Bae, J. Lee, G. M, Lee, N. Crespi, & J. K. Choi: Minimizing the Number of IGMP Report Messages for Receiver-driven Layered Video Multicasting. IEEE VTC spring, May (2011).
12. Hugh W. Holbrook and David R. Cheriton.: IP multicast channels: EXPRESS support for large-scale single-source applications. In Proceedings of the conference on Applications, technologies, architectures, and protocols for computer communication (SIGCOMM '99). ACM (1999).