Assessing the Impact of Network Performance on Popular E-Learning Applications

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***Abstract*—With the outbreak of COVID-19 pandemic, several educational and business organizations have adopted online video conferencing platforms to facilitate their smooth functioning. These platforms have largely favored educational institutions for remotely conducting virtual classes over various electronic learning (e-learning) platforms. This has imposed challenges on existing Internet platforms for efficiently managing network performance generated from the extensive use of these platforms. In this paper, a framework for monitoring the effect of different network parameters, while using some well-known e-learning platforms is provided. The different LTE network performance parameters like uplink speed, downlink speed, network latency, and jitter are considered. We observed that the LTE network performance parameters obtained while using Microsoft Teams is optimum. Since, we observed that Microsoft Teams provided an optimal performance, we further perform analysis on Microsoft Teams. We further obtain the empirical distribution pertaining to the LTE network communication features by employing Gamma distribution. From our analysis, it is observed that the network throughput, latency, and jitter can be optimized to enhance the users' quality of experience by employing the proposed strategy.**

***Index Terms*—E-learning, LTE network performance analysis, COVID-19, Network Latency, Gamma Distribution, 4G-LTE.**

I. Introduction

The unprecedented outbreak of COVID-19 has contrived several governments across the world to impose restrictive measures for minimizing public's exposure to the virus. Among these measures, a major resolution was to enforce remote functioning of academic institutions and offices [1], [2]. This resulted in the large-scale usage of electronic platforms for exchanging information among multiple users. These platforms have benefitted the academic, public, and commercial sectors to function smoothly amidst the pandemic's outbreak.

A major breakthrough in this scenario was to facilitate electronic learning (e-learning) systems for fostering education system in universities, schools, and other educational institutions during the outbreak of COVID-19 [2]. This somehow assisted in extending the learning process by exchanging academic learning materials digitally and conducting online active learning sessions. The extensive use of these electronic platforms for digitally exchanging information across multiple clients and servers has challenged the LTE network communication characteristics of Internet platforms, hence affecting the users' quality of experience [2], [3].

In this paper, a methodology for acquisition of LTE network communication features from four popularly used video conferencing platforms, widely used these days as a mode of e-learning platform i.e., Google Meet, Zoom Cloud Meetings, Cisco Webex Meetings and Microsoft Teams is presented. The observations made from our analysis like the uplink and downlink speeds during the usage of these e-learning platforms, network latency, and jitter are studied in a stratified manner for each considered platform. Further, the LTE network communication features collected over multiple traffic instances are considered and modelled using the Gamma distribution [4]. A comprehensive account of some recent and cutting-edge scientific works conducted in this direction is presented. Further, the popularity and platform dependency of the four considered e-learning platforms is presented. In summary, this work testifies the efficacy of e-learning systems in-context with the present COVID-19 scenario and proclaims the requirement for efficient connectivity in these e-learning platforms to improve the users' quality of experience.

In Fig. 1, the analysis of google trends data has been provided for four video conferencing platforms also popularly adopted for interactive e-learning with the search terms as "Google Meet", "Zoom App", "Cisco Webex", and "Microsoft Teams". It is observed that based upon the statistics from Google, there is a remarkable rise in the utilization of these online platforms since mid February 2020. This was the timeframe when several countries across the world started imposing stringent measures in controlling the spread of COVID-19 through rigorous lockdown and other social isolation measures. Hence, it is clear that the large-scale adoption of these platforms has been witnessed post COVID-19 outbreak essentially in most of the sectors. Further, the popularity of "Google Meet" and "Microsoft Teams" is observed to be the maximum.

II. Related Works

This section addresses some recent works conducted upon e-learning platforms and their rising utility following the outbreak of COVID-19 pandemic. Dhawan [3] presented

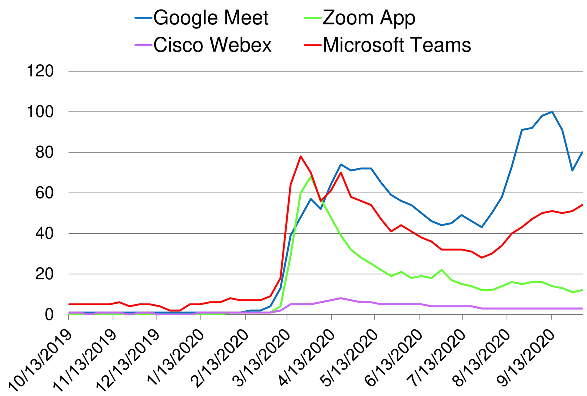


Fig. 1: Popularity analysis of "Google Meet", "Zoom App", "Cisco Webex", and "Microsoft Teams".

the inevitability of e-learning during the pandemic situation that arose due to COVID-19. The author performed SWOC analysis on online teaching-learning modes adopted in India that epitomized strengths, weaknesses, opportunities and challenges. The advent in Edtech startups during such a pandemic situation was presented. Further, ways to tackle challenges due to execution of e-learning modes were presented. The article also focused on presenting the proficiency of e-learning during natural calamities. Radha et al. [5] conducted a google form based survey on undergraduate students to collect data by performing stratified sampling method. The prime motive of the article was on scrutinizing the attitude of students towards e-learning environments. A questionnaire designed using google forms was distributed globally among undergraduate students and 175 samples were selected for study. The authors observed that 82.29% students were willing to learn through e-learning environment whereas only 5.14% students were reluctant to learn through e-learning due to connectivity issues. Many such questions were individually analyzed to study the global trend of e-learning among students.

Deshpande et al. [6] conducted an informative survey for the 4G-Long Term Evolution (LTE) network users. The authors used NetVelocity application to compare two largest 4G service providers in India i.e., Bharti Airtel and Reliance Jio. The network performance parameters used to compare the two service providers included reference signal received power (RSRP), signal interference plus noise ratio (SINR) and network throughput. The authors after analyzing the network performance parameters concluded that Bharti Airtel showed better SINR range and throughput as compared to Reliance Jio. Feldmann et al. [7] aggregated data from varied sources of vantage points and scrutinized LTE network communication shifts affected due to lockdown imposed during COVID-19 pandemic. Further, the authors studied the top 15 hypergiants (networks having higher outbound traffic) within the considered vantage points. Analysis of transport layer was presented focusing on various domains like video conferencing, TV streaming, e-mail and many such. Shahzad et al. [1] studied the accessibility of e-learning portals based on gender of the user i.e., either male or female. The study focused on analyzing parameters including service quality, user satisfaction, information quality, system use, system quality, and e-learning portal success. The authors used partial least squares structural equation modelling technique to analyze data collected using google forms from 280 students participating from various Malaysian universities. Certain specific relationships between the considered parameters were scrutinized for both male as well as female accessibility of e-learning portals.

III. Materials and Methods

This section entails the detailed specifications of the popularly used e-learning applications, scrutinizes the network performance parameters used to evaluate the impact of network performance on e-learning platforms and methodology used.

A. *E-learning Applications*

Popular platform-independent video conferencing platforms that have gained immense popularity these days as a mode of e-learning paradigm, used in our study includes Google Meet, Zoom Cloud Meetings, Cisco Webex Meetings, and Microsoft Teams. The platforms on which the considered e-learning applications are compatible with are summarized in Table I. The size specifications of the mentioned applications based on different operating systems are summarized in Table II. It can be observed that Google Meet seems to be of the least size in Android OS. However, it directly runs using web browser and doesn't require any prior installation in Windows environment. Further, for iOS Zoom Cloud Meetings claims the least size as compared to all other applications. Although size of the application doesn't have much impact on the performance still moderate application size is recommended for better optimized and quality-conscious applications. Present day video conferencing tools have multiple common features like sharing presentation screen, video and audio buttons, and platform independency. These features enable a suitable environment for creating virtual classrooms, business and organizational meetings, etc. Also, during such an ongoing pandemic situation such applications are gaining popularity and we try to compare these applications based on certain qualitative network performance parameters.

TABLE I: Platform compatibility of considered e-learning applications.

Application	**Android OS**	**iOS**	**Windows**	**Web**
Google Meet	✓	✓	✗	✓
Zoom Cloud Meetings	✓	✓	✓	✓
Cisco Webex Meetings	✓	✓	✓	✓
Microsoft Teams	✓	✓	✓	✓

✓- Platform compatible, ✗- Platform incompatible
* N/A - Not Applicable

TABLE II: Size specifications of considered e-learning applications based on different operating systems.

Application	Android OS	iOS	Windows
Google Meet	13.04 MB	143 MB	N/A*
Zoom Cloud Meetings	28.79 MB	117.7 MB	13.5 MB
Cisco Webex Meetings	53.83 MB	218.1 MB	93.9 MB
Microsoft Teams	52.28 MB	233.8 MB	96.6 MB

B. Network Performance Parameters

The experimentation was conducted with the assistance of 4G-LTE network type with a frequency spectrum of 2300 MHz. The network specifications of the experimental device includes physical cell identity (PCI) which is 143, cell global identity (CGI) i.e., 367122 and type allocation code (TAC) 44. Network plays a crucial role in determining the overall quality of the applications under consideration. Since e-learning applications mostly deal with presentations being widely shared live among a group, video quality matters a lot which is dependent on network performance. Thus, certain network performance parameters selected for the study includes downlink speed, uplink speed, latency and jitter. The two-way communication between the base transceiver station (BTS) and user equipment can be realized through downlink speed and uplink speed where the former represents the signal transfer from BTS to the user equipment and the latter signifies the obverse i.e., signal transfer from user equipment to BTS [8]. The time interval taken to transmit a packet from source to destination is epitomized by the term latency i.e., also in networking terms called as ping [9]. Lower latency is recommended for a better network performance and several factors due to which higher latency is observed includes network congestion, location of BTS, and many such. The rate at which latency varies as per time is defined as jitter which is affected by factors like network congestion, hardware constraints, site crash and many such [10]. Jitter in turn induces packet loss which causes call drops, video buffering and many such network performance degradation issues.

C. LTE Communication Distribution Model

Here, we consider Gamma distribution which is a popularly used distribution for modelling positive valued datasets which inherently possess a skewed distribution [4], [11]. In order to model the Gamma distribution for LTE communication data acquired corresponding to our considered e-learning platforms, we denote the variable X to represent the LTE network communication features which we wish to model. Now, X is said to be Gamma distributed if,

$$X \sim Gamma\left(\alpha, \beta\right), \tag{1}$$

where α and β represent the respective shape and rate parameters for the distribution obtained in Eq. (1). Here, α and β are responsible for representing the shape and range corresponding to the distribution of X.
Now the probability distribution function (PDF) for the above distribution can be given as,

$$p\left(x\right) = \frac{\beta^{\alpha} x^{\kappa} \exp\left(\beta x\right)}{\Gamma\left(\alpha\right)}, \tag{2}$$

where $x > 0$, $\kappa = (\alpha - 1)$, and $\Gamma\left(.\right)$ represents the gamma function. Here, the shape and rate parameters i.e., α and β, are both positive ($\alpha > 0$, $\beta > 0$). The mean (μ) and standard deviation (σ) corresponding to Eq. (2) are represented as,

$$\mu = E\left[X\right] = {}^{\alpha}\!/\!_{\beta}, \tag{3}$$

$$\sigma = \sqrt{Var\left[X\right]} = {}^{\sqrt{\alpha}}\!/\!_{\beta}. \tag{4}$$

From the expressions obtained in Eq. (3) and Eq. (4), we can compute the mean and standard deviation parameters for the LTE network communication features.
The cumulative distribution function (CDF) for X can be obtained by considering the integration of the expression in Eq. (2) as,

$$P\left(x\right) = \int_{0}^{x} p\left(x\right) dx. \tag{5}$$

D. Methodology

In order to measure the network performance parameters, we used NetVelocity application on Android OS. The device specifications for the client device is summarized in Table III. The methodology we adopted in order to monitor the effect of certain network performance parameters like downlink speed, uplink speed, latency and jitter while using the considered e-learning applications are as follows:

- Step-1: Installation of NetVelocity application on the client device and checking of the base network parameters like network type, PCI, CGI and TAC.
- Step-2: Installation of Google Meet, Zoom Cloud Meetings, Cisco Webex Meetings and Microsoft Teams.
- Step-3: Requesting the host device to send meeting links to join.
- Step-4: Sending acknowledgement from client device by joining the meeting using meeting link sent by the host device.
- Step-5: Joining meeting sessions individually for each application for equal time intervals of 8 minutes each.
- Step-6: Switching to NetVelocity application and continuously monitoring network performance parameters i.e., downlink speed, uplink speed, latency and jitter for 8 consecutive iterations.
- Step-7: Visualizing the observed network performance indicators while using each e-learning application and corresponding CDFs and PDFs obtained with the aid of Gamma distribution for the e-learning application epitomizing best network performance.

TABLE III: Specification of the client device on which experimentation is performed.

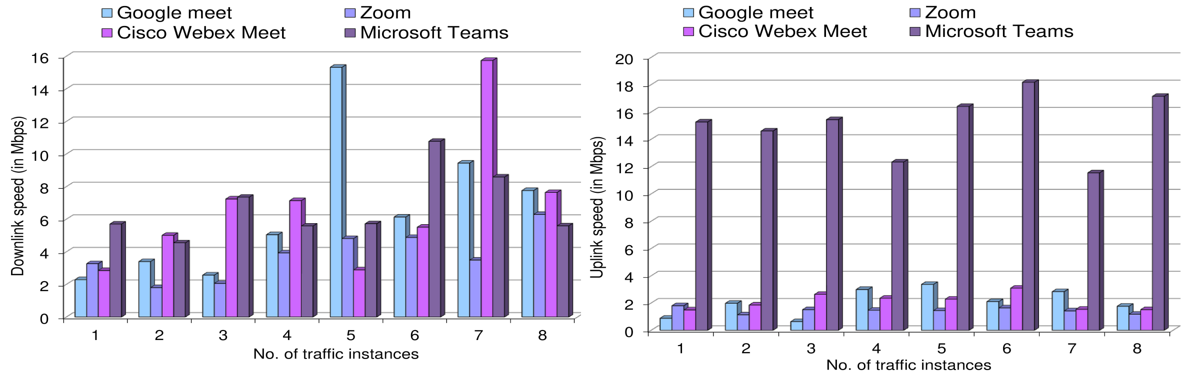
Operating System	Processor	RAM	Storage
Android 10 OS	Qualcomm Snapdragon 720G	6 GB	64 GB

IV. Experimental Results

In this section, empirical results obtained by carrying out the above experimentations over four e-learning applications are presented. Here we comparatively study the network performance parameters like uplink and downlink speed, network latency, and jitter for a 4G-LTE network. In Fig. 2, the fundamental network features collected from our experimental analysis for four e-learning platforms with respect to eight traffic instances are presented. Here, Fig. 2(a), provides the downlink speed expressed in Mbps corresponding to four e-learning platforms $viz.$, Google Meet, Zoom Cloud Meetings, Cisco Webex Meetings, and Microsoft Teams. In Fig. 2(b), the uplink speed for eight traffic instances is provided. It is observed that the uplink speed obtained while using Microsoft Teams is substantially higher as compared to other platforms providing a speed of more than 10 Mbps for all eight instances. However, the other three applications provided a very borderline uplink speed which failed to exceed an uplink speed limit of 4 Mbps.

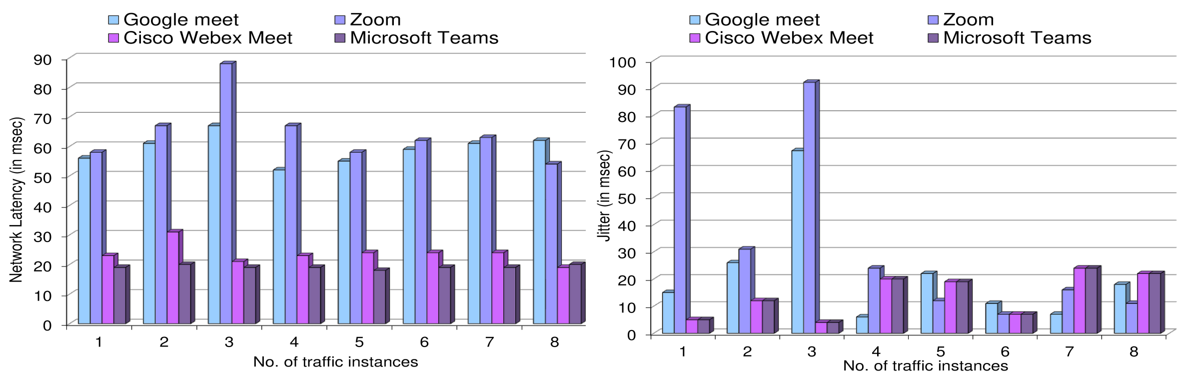
From Fig. 3 the network performance parameters for LTE network communication are obtained. Fig. 3(a), provided the network latency expressed in milliseconds (msec) for all four e-learning platforms. It was observed that use of Microsoft Teams provided a very promising performance with network latency below 20 msec for all traffic instances. Finally, in Fig. 3(b) the respective jitter values (expressed in msec) were presented. It was observed while experimenting on Cisco Webex Meetings and Microsoft Teams that minimum jitter values without exceeding 25 msec for all traffic instances were obtained.

The results for illustrating empirical distribution of traffic features are illustrated in Fig. 4 and Fig. 5. From the above observations, it is inferred that Microsoft Teams provided optimal performance in terms of the LTE network communication parameters considered in this study. Therefore, we model the downlink and uplink speed for Microsoft Teams platform for the continuous traffic traces acquired from our experimentation. In Fig. 4(a), we observe the difference in probability distribution for downlink speed for different shape and rate parameters i.e., for $\alpha = 1.0, 1.5, 2.5$ and $\beta = 1.5, 2.0, 1.0$. The cumulative distribution for downlink speed is provided in Fig. 4(b) for the same shape and rate parameters. The probability distribution for uplink speed is provided in Fig. 5(a) for different values of α and β. Finally, in Fig. 5(b), the cumulative distribution for the uplink speed is presented. Here, it is worth noting that for $\alpha = 1$, the distribution converges to an exponential distribution, and for rate parameter $\beta = 1$, the distribution is said to follow a standard Gamma distribution. From Fig. 4 and Fig. 5, it is evident that the skewness of distribution is heavily influenced by shape parameter α and the skewness reduces considerably with increase in value of parameter α.



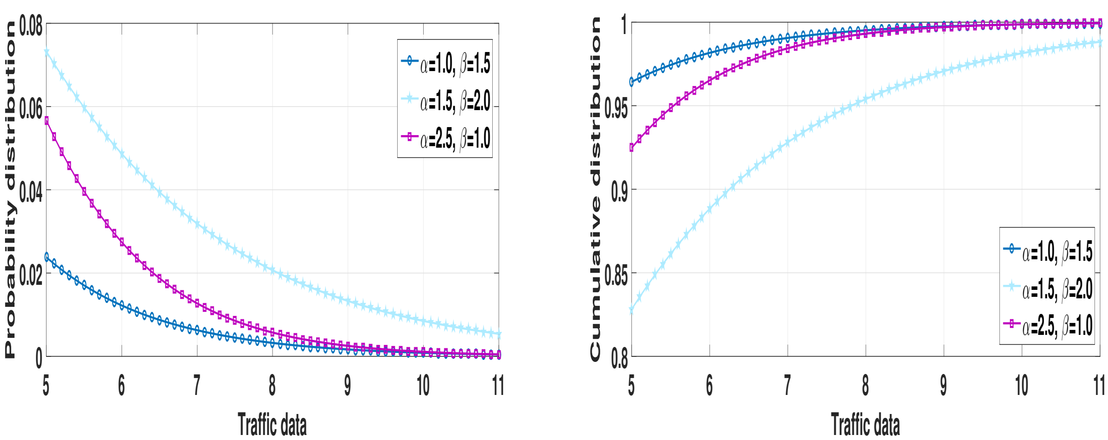
(a) (b)

Fig. 2: LTE network communication parameters observed while using four e-learning platforms. Fig. 2(a) Downlink speed expressed in Mbps for eight traffic instances; Fig. 2(b) Uplink speed of the network corresponding to four e-learning platforms expressed in Mbps.



(a) (b)

Fig. 3: LTE network performance parameters observed while using four e-learning platforms. Fig. 3(a) Network latency (in msec) observed while using the e-learning platforms for different traffic instances; Fig. 3(b) Jitter in msec for eight traffic instances.



(a) (b)

Fig. 4: Representation of empirical distribution for downlink speed of the network features corresponding to shape and rate parameters $\alpha = 1.0, 1.5, 2.5$ and $\beta = 1.5, 2.0, 1.0$ respectively. Fig 4(a) Probability distribution plot for downlink traffic features; Fig. 4(b) Cumulative distribution for downlink traffic features.

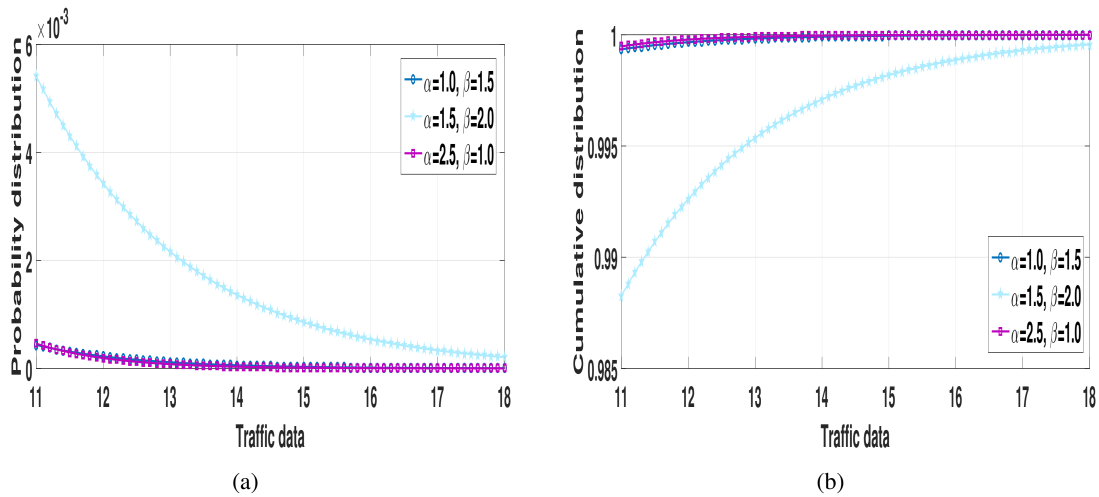


Fig. 5: Representation of empirical distribution for uplink speed of the network features corresponding to shape and rate parameters $\alpha = 1.0, 1.5, 2.5$ and $\beta = 1.5, 2.0, 1.0$ respectively. Fig. 5(a) Probability distribution for uplink traffic; Fig. 5(b) Cumulative distribution for uplink traffic.

V. Concluding Remarks

The outbreak of COVID-19 pandemic globally impacted not only the education system but also socio-economic sectors. In such an unprecedented situation, e-learning proves itself a boon for educational institutions as well as business organizations. We considered four popularly known e-learning applications i.e., Google Meet, Zoom Cloud Meetings, Cisco Webex Meetings and Microsoft Teams for study. These e-learning applications completely rely upon network performance since the presentations and videos being shared needs to be qualitative in order to substitute classroom teachings, business meetings, etc. This paper focused on analyzing network performance parameters like downlink speed, uplink speed, latency and jitter observed while using considered e-learning applications. Also, certain relevant works in this domain were epitomized. We observed that the network performance parameters are significantly optimum while using Microsoft Teams. Thus, we employed Gamma distribution to obtain the PDFs and CDFs for the underlying LTE network communication features for different values of α and β. We observed that the skewness and range of distribution is substantially influenced by the selection of shape and rate parameters (i.e., α and β). Therefore, the observations made from the empirical distributions of LTE network communication features provide futuristic scope for improvising network throughput and minimizing latency as well as jitter.

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