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Study on transmission quality in cellular 4G and 5G networks between 2019–2021: Impact of the COVID-19 pandemic on the level of provided services by operating base transceiver stations

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Abstract

The COVID-19 pandemic has significantly limited user mobility, not least among students. Remote learning had a particular impact on resource allocation in relation to using terrestrial cellular networks, especially 4G systems in urban agglomerations. This paper presents the results of a quality evaluation of an outdoor environment, carried out between 2019 and 2021 on the campus of a technical university. Annual studies are conducted using our own custom-built mobile application, installed on 50 mobile devices (i.e., smartphones) running Android OS. This study aims to determine the impact of reduced user mobility on access parameters in mobile networks, that is, both download and upload throughput as well as delay (ping), with a particular focus on serving base transceiver stations (BTSs). This research scenario involves long-term evolution (LTE) compatible user equipment (UE) that operates under four Polish mobile network operators (MNO), which includes roaming connections and the newly launched 5G standard.

Introduction

The ongoing COVID-19 pandemic has reduced user mobility considerably. Many people have sacrificed free movement due to health reasons, personal reasons, or other issues. This fact especially applies to university students who had to switch to distance learning. These factors have certainly forced the necessity to reorganize the mechanisms for allocating resources in terrestrial cellular networks.

This paper presents the results of the measurements made during the yearly studies on the quality of transmission on the campus of a technical university. The research covers the years from 2019 to 2021, conducted in an outdoor environment and an open space. The measurements were made using our own custom-built mobile application, running on Android-powered user equipment (UE). Each year, the measurement campaign covered a group of 50 mobile devices in the form of smartphones, in accordance with the parameters of the long-term evolution (LTE) standard. In the following years, tests also involved roaming devices as well as user equipment compatible with 5G networks.

This kind of measurement methodology (referred to as crowdsourcing) is flexible, controllable, and independent of the measurement systems of commercial companies (NSC, 2023; RSC, 2023; SPABC, 2023), which significantly reduces the costs of conducting research. It should be emphasized that such tests relate to the quality of network (QoN) level and are, therefore, related to measurements of the access layer parameters of the tested network. The second level of testing may be referred to as quality of service (QoS), where the higher layers of the logical network model, and therefore the applications implemented in them, are considered. Their quality definitely plays a major role. This type of research is, however, very complex and time-consuming and requires specialized techniques and measuring devices (Nowicki & Uhl, 2017). Of course, most of these tools are licensed, which means they are expensive.

For example, measurement of packet loss, jitter, bit error rate, or frame error rate (BER/FER) would require a dedicated connection as well as additional applications installed on both UE and servers to return the transmitted packets (i.e., test data). This is almost impossible in the measurement environment used in this work, which includes a commercial fully operational terrestrial cellular network. Therefore, the QoS level will not be used here. There is one more level used to test the quality of provided services, i.e., quality of experience (QoE). Here, the end user plays an important role, who subjectively assesses the quality of a particular system or service and presents the results of their assessment in terms of the mean opinion score (MOS) scale. To investigate such a scenario, it would be necessary to ensure that all participants undertook the test simultaneously, at the same place and with the same content. Such a situation would be idealistic and, therefore, could not be guaranteed. For this reason, this level of research will also not be investigated further here. However, the present authors plan other research campaigns in the near future.

The main contributions of this paper are as follows:

- First, we discuss how the global pandemic has limited user mobility, which has enormously impacted the methods for consuming content and exchanging information online in a remote form.
- Next, we present a review of recently published works, which focus on technical network quality as well as subjective user-related aspects that occurred during the last few years.
- Later, we describe our research campaign, carried out between 2019 and 2021, which was conducted in an outdoor environment and involved 50 mobile devices each year.
- Afterwards, we investigate the obtained results related to serving BTSs, including download, upload, and ping for 4G- and 5G-compatible UE, as well as both domestic and roaming users.
- Finally, we conclude our manuscript with possible suggestions and feedback that might improve the efficiency of allocating and managing network resources, including future study directions.

After a short introduction, we describe previous studies on various quality aspects, including QoN, QoS, and QoE analyzes. The measuring environment, along with a description of the materials and methods used, is discussed in the next section. The section that follows is devoted to the core of this work: the presentation and interpretation of the results. The penultimate section includes a discussion on UE results, which considers both domestic and roaming devices, as well as UE and BTSs with 5G connectivity. The work concludes with a summary section, which includes an insight into further research.

Literature review

User mobility becomes a major issue when an extensive spreading of human infections occurs. Currently, there are several models developed that aid the performance of wireless networks. In one study (Hernandez-Orallo & Armero-Martinez, 2021), the authors propose a number of mobility models for evaluating the risk of transmitting COVID-19, which are based on various urban scenarios. The results show that it is possible to obtain a heat map along with the exposure risk. Such studies are interesting not only for network providers, but also for state and local authorities.

Nowadays, cloud-based service providers are facing a major challenge in order to meet the growing demands of users. During the pandemic, millions of citizens were advised to stay at home to prevent the spread of the disease. The global pandemic forced telecom operators and service providers to optimize connection mechanisms as well as supply cutting-edge computing technologies to handle network traffic. Of course, the evaluation of systems and services, especially from the user side, is based on a variety of attributes, most often expressed as the ratio between price and quality (Yassine & Hossain, 2022).

Advances in wireless networks and mobile technologies, including 4G/5G, Bluetooth, Wi-Fi, etc., have made intelligent and smart services available for literally everyone. Most often, they are related to lifestyle and health monitoring. As we know, deep learning (DL) or machine learning (ML) services require extensive computational resources, which is clearly visible in terms of higher energy consumption. Therefore, offloading tasks become an interesting field of study to investigate (Aazam, Zeadally & Flushing, 2021).

The exponential growth of multimedia content consumption worldwide has led to a huge increase in data traffic. With the outbreak of the COVID-19 pandemic, video conferencing platforms like Clickmeeting, MS Teams, Zoom, etc., as well as streaming platforms such as Netflix, Twitch, YouTube, etc., caused pressure on various wireless and wired network environments. To mitigate the negative QoE experience, the deployment of small cells (femtocells) in 5G technology, instead of typical macrocells, was proposed (Anand, Togou & Muntean, 2022b). In this work, the authors introduced the machine learning interference classification and offloading scheme (MLICOS) method. The performance of MLICOS was evaluated using several metrics, namely, peak signal-to-noise ratio (PSNR), structural similarity index measure (SSIM), and video multi-method assessment fusion (VMAF). Next, it was compared to various scheduling algorithms, that is, proportional fair (PF) and variable radius and proportional fair (VR+PF), as well as a cognitive approach (CA).

In another paper (Lin et al., 2016), the authors proposed a QoE-based service-aware resource scheduling (SARS) scheme for multi-mode wireless terminals. The virtualization of radio access networks enables efficient bandwidth resource management in order to provide the optimal user experience beyond acceptable QoS values, particularly in the case of popular video streaming services. SARS creates a new customer-centered network approach, which can achieve both higher bandwidth efficiency and a satisfying user experience.

The aim of this survey (Adil & Khan, 2021) is to outline emerging healthcare IoT applications during the COVID-19 pandemic between 2019–2021 in terms of network architecture security, i.e., different network layers and secure communication environments, including trustworthiness, authentication, and data preservation. This paper comments on existing challenges and open issues, as well as future research directions in sustainable smart cities.

All in all, one should keep in mind that the success of a mobile application or service depends not only on QoE, but also on the QoS aspects. However, a proper and reliable evaluation has to consider a complex set of factors, including technical specs of the user equipment as well as network performance and heterogeneity. Another aspect is the environment in which the content is consumed (Laso et al., 2022).

Methodology

Research environment

Gdansk University of Technology is one of Poland's largest technical universities. Every year, it attracts about 20,000 full-time and extramural students to enroll for BSc (Bachelor of Science) courses, MSc (Master of Science) courses, as well as PhD (Doctor of Philosophy) students taught at the traditional Doctoral and Implementation Doctoral Schools. The university has over 2,500 employees, including approximately 1,200 scientists. This research campaign was conducted during term time of the academic years 2019, 2020, and 2021 in the open areas of the main Campus of the Gdansk University of Technology, as shown in Figure 1. The campus comprises 8 faculties and 77 hectares of urban space. Undoubtedly, this is an interesting place to conduct research on QoS and QoN in terrestrial cellular systems.

The matter of ensuring appropriate quality, including a high bitrate in both download and upload as well as a low delay level, is crucial in the implementation of real-time services, such as the transmission of speech signals, videoconferencing, and various audio-visual multimedia streaming. It is particularly important to consider the growing number of users, availability of mobile devices, ubiquity of wireless networks, and increasing expectation of efficient and reliable services (Elsayed, Le-Khac & Jurcut, 2021).

It is worth mentioning that modern mobile devices offer much more than just the exchange of short message service (SMS) text information, multimedia messaging service (MMS), or the transmission of speech signals. Smartphones offer wide possibilities for communication besides sharing and consuming all kinds of content (Lutu et al., 2020). They have several integrated sensors and wireless communication modules. A lot of information about their status, operating mode, and current indications can be interpreted from the number and type of mobile applications installed on the subscriber's device.

Figure 1. Campus of the Gdansk University of Technology (GUT, 2023)

User activity and mobility

The impact of the COVID-19 pandemic has been felt throughout most of the world. It made almost all educational institutions resort to lockdowns for indefinite periods, with teachers having to adopt online learning methods while students had to adapt quickly to distance learning environments (Syauqi, Munadi & Triyono, 2020). The outcome was a new type of learning, called digital learning, which can take the form of e-learning and m-learning technologies. A key element in reducing student dropout rates in the virtual learning environment is to monitor the degrees of commitment and satisfaction experienced by students during learning (Korchani & Sethom, 2022).

In 2019–2021, numerous university classes were conducted in a remote or mixed (hybrid) mode. The lectures usually took place using streaming platforms, such as Clickmeeting, MS Teams, and Zoom (Favale et al., 2020). Owing to the continued rapid spread of COVID-19, lockdown measures were imposed in many countries. Many organizations found themselves forced to devise measures to remain operational during the pandemic and afterwards. Thanks to video conferencing, many institutions allowed employees to work from home. Consequently, cloud service providers noticed a surge in the usage of their solutions (Rananga & Venter, 2020).

As we know, real-time services require a harmonious balance of network and application dynamics to provide a satisfactory user experience. However, providers' monitoring and optimization of QoS parameters in networks have traditionally lacked knowledge about users' QoE, and providers have, as a result, always been slow to improve user experience (Carofiglio et al., 2021).

Real-time service measurements

The requirements for typical real-time audio-video transmission services are presented in Table 1. With this in mind, we decided to investigate how network resources are distributed between individual base transceiver stations (BTSs) and mobile devices located within a selected area of a technical university campus.

Table 1. Popular multimedia services and their technical requirements

Service	Bitrate [Mbps]	Delay [ms]
Video conferencing	1–4	100
SD streaming	3–4	100 (real-time); 300 (buffered)
HD streaming	5–8	100 (real-time); 300 (buffered)

The unprecedented increase in the use of mobile broadband as an essential means of Internet connectivity has made a corresponding, scalable evaluation and appraisal of QoE of applications delivered over LTE networks indispensable. However, direct QoE measurements are notoriously time consuming and resource intensive. Furthermore, the wireless nature of LTE terrestrial networks means that QoE must be evaluated in multiple locations per base station since factors such as, for example, signal availability might be subject to considerable spatial variations (Adarsh et al., 2021).

For three years running, tests were carried out using 50 smartphones from several manufacturers, various technical specifications, and different versions of the Android operating system. The investigation was performed using our custom-built mobile application throughout the week at different times of the day. Each person took measurements at 10 different points (with more than 30 measurements at each point); these were evenly distributed across the premises of the campus. The weather was sunny, with no strong winds, clouds, or precipitation; temperatures ranged between 15°C and 25°C.

Results

The measurement results were first stored in the internal memory of each mobile device, and then transferred to a database for processing and analysis. Of course, all UE were compatible with the LTE standard and this mode of operation was imposed on each mobile device. The data obtained was processed using the analysis of variance (ANOVA) statistical method, with the confidence level set to 0.95. It is worth noting that obtained confidence intervals for measured parameters were always less than 10% of their average values. This proves that a sufficiently large number of measurements have been made in order to treat obtained results as reliable. To further check the statistical significance of performed measurements, one could also attempt to determine Cronbach's alpha, which measures internal consistency (Lord & Novick, 2008). However, Cronbach's alpha presumes item homogeneity without testing this assumption. Therefore, instead of this coefficient, congeneric reliability is increasingly used, which does not presuppose this homogeneity. For the duration of the studies, considering this particular scenario and the urban nature of the area, the group of serving base stations comprised six BTSs originating from all four main mobile network operators (MNOs) in Poland. The results, in the form of throughput (downlink and uplink) and delay (ping), are shown in Figures 2 to 10. The results from 2019, which cover mean and median download, upload, and ping, are presented in Figures 2 to 4.

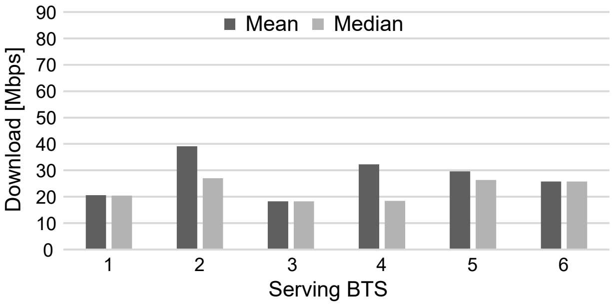

Figure 2. Download speeds of serving BTSs in 2019

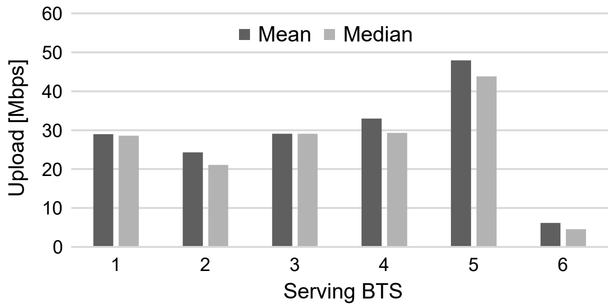

Figure 3. Upload speeds of serving BTSs in 2019

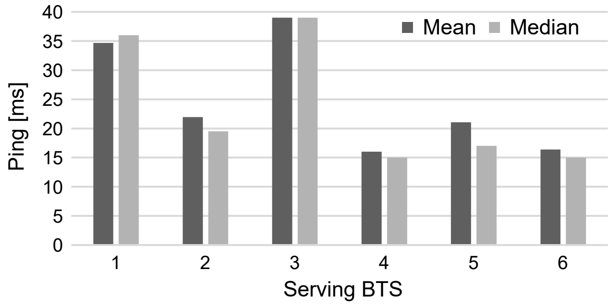

Figure 4. Ping values of serving BTSs in 2019

The results from 2020, which similarly accounted for download, upload, and ping, are presented in Figures 5 to 7.

Finally, the results from 2021 are shown in Figures 8 to 10.

Examining Figures 2, 5, and 8, it can be concluded that, in 2019, the value of the downlink bandwidth, averaged over all six BTSs, was approximately 30 Mbps. In 2020, it was almost 50 Mbps;

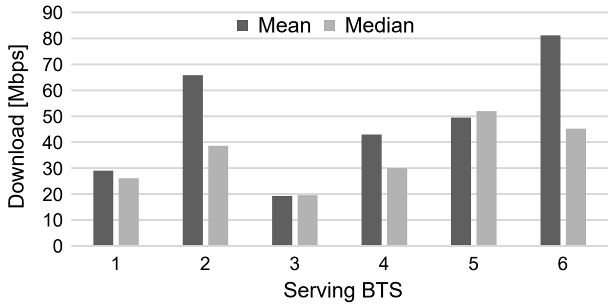

Figure 5. Download speeds of serving BTSs in 2020

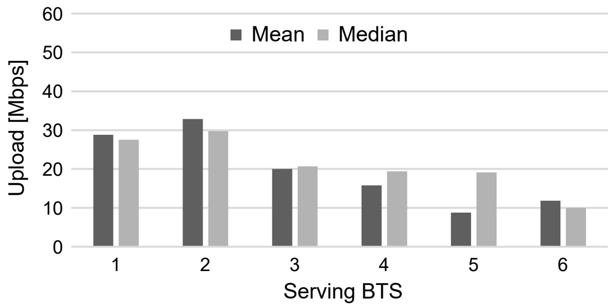

Figure 6. Upload speeds of serving BTSs in 2020

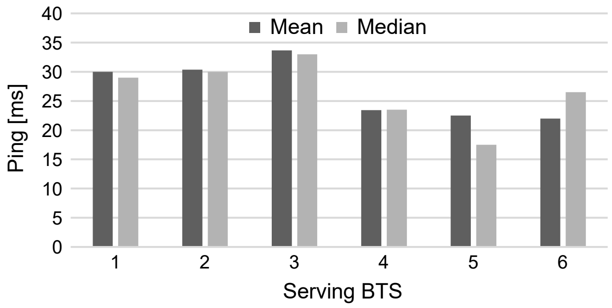

Figure 7. Ping values of serving BTSs in 2020

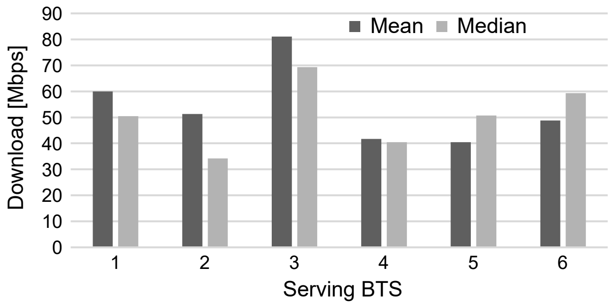

Figure 8. Download speeds of serving BTSs in 2021

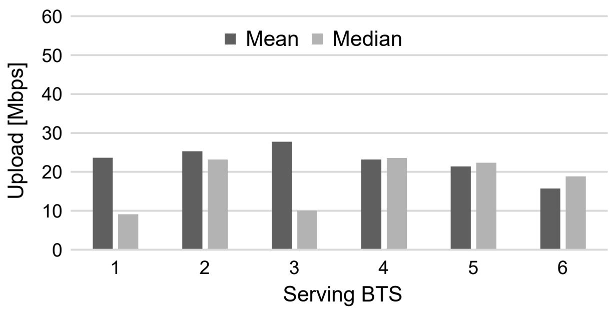

Figure 9. Upload speeds of serving BTSs in 2021

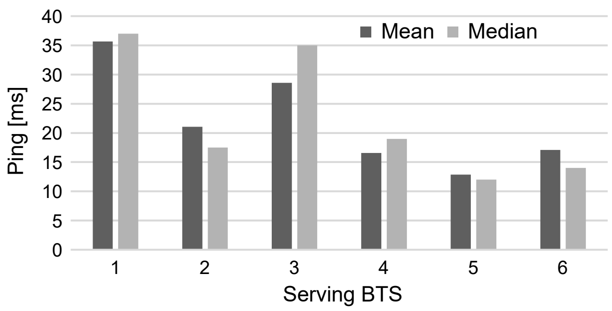

Figure 10. Ping values of serving BTSs in 2021

in 2021, it fluctuated at approximately 55 Mbps. As can be observed, the bandwidth offered by operating BTSs was greater when fewer users were logged into the mobile network (for full stationary work at the university in 2019, a gradual changeover to remote work in 2020 onwards, and full remote work in 2021). There were no significant differences in the bandwidth offered by operating BTSs, which, as indicated in the introduction, belonged to 4 different cellular network operators.

From Figures 3, 6, and 9, it can be concluded that the value of the uplink bandwidth, averaged over all six BTSs, was approximately equal to 30 Mbps in 2019, nearly 20 Mbps in 2020, and fluctuated at around 23 Mbps in 2021. Finally, a reverse trend to that of the downlink can be observed. With fewer users logged into the cellular network, the data transfer rate is slower in the uplink direction. This could be due to the increased amount of data (mobile multimedia content) provided (created) by end users. Their increased remote work probably entailed the sharing of their own images from a desktop PC or a selected application, voice communication and, of course, posting report files on a dedicated remote e-learning platform.

When examining the values of average delays in the cellular network in the analyzed time period (see Figures 4, 7, and 10), they are found to fluctuate around 25 ms in 2019, 30 ms in 2020, and 25 ms in 2021. Here, no significant correlation can be found between the delay value (ping) and the number of simultaneously active users in the campus area. This is probably because the number of queries to remote e-learning servers and related document repositories did not change. However, the location of the source (user equipment), i.e., the place where queries were generated, indicates the so-called home office working mode.

It is worth noting that the values of both bandwidth and latency measured in 2019–2021 were significantly higher than the required values of these parameters from Table 1, necessary for well-functioning real-time applications over the Internet. This confirms the good dimensioning of the networks installed on the campus by various MNOs.

Discussion

Clearly, restricting the mobility of the general population slowed down the spread of the COVID-19 pandemic. Tracking the location of individuals helped to tailor effective mobility limitation policies and enhanced the prediction of potential hotspots. It improved the alerting of individuals who might have been exposed to the virus. Owing to the widespread use of mobile devices within the population, cellular networks are a valuable asset for such purposes (Khatib et al., 2021).

Roaming Users

In 2020, we hosted a group of Erasmus students from abroad at our university. Thanks to this, we could investigate network performance for roaming services. Figures 11 to 13 show the obtained measurement results, which also considered throughput (downlink and uplink) and delay (ping), for three BTSs with the roaming service.

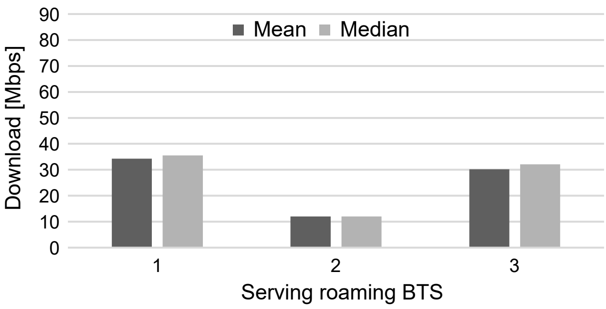

Figure 11. Download speeds of serving roaming BTSs in 2020

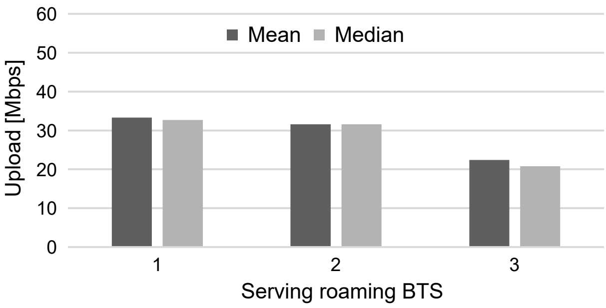

Figure 12. Upload speeds of serving roaming BTSs in 2020

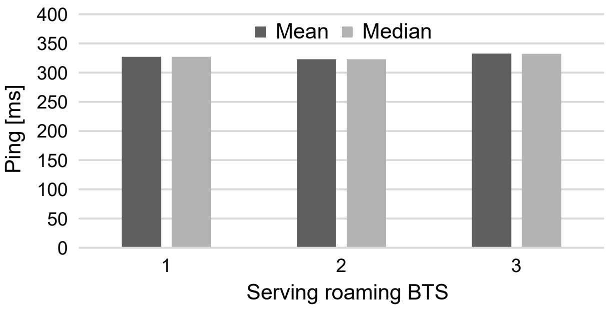

Figure 13. Ping values of serving roaming BTSs in 2020

The diagrams in Figure 11 show a two-fold decrease in the average throughput of mobile channels in the downlink direction, compared with the case of BTSs without roaming (25 to 50 Mbps). Especially BTSs no. 2 is significantly different from the average value of 25 Mbps. It can be seen here that a roaming connection running through mobile networks operating in different countries has a significant impact on the download bandwidth. This cannot be seen in the case of capacity in the upload direction (see Figure 12). Here, all three BTSs show comparable bandwidth with an average value of 27 Mbps. It is slightly higher compared with bandwidth in networks without the roaming service (23 Mbps). The reason for this might be a smaller amount of data transmitted in the uplink direction, which entails a lower load on the mobile channels used for the selected connection. On the other hand, Figure 13 shows a significant difference, representing the delay time in networks with the roaming service. This delay is ten times greater than that of a network without the roaming service. It can be seen here that the connections running through the networks of various international operators significantly impact the ping value, which is self-evident.

5G-compatible UE

In view of increasing data demand, mobile broadband (MBB) has become a primary goal of 5G networks. MBB aims to provide very high-speed Internet access across seamless connections. Existing cellular systems, including 3G and 4G networks, also require monitoring to ensure acceptable network performance. Therefore, any analysis of existing MBB will assist MNOs in improving their services even further, thus ensuring user satisfaction (El-Saleh et al., 2022).

In 2021, a group of domestic students already possessed 5G-compatible smartphones. Therefore, it was interesting to determine the extent of resources that recently launched 5G serving BTSs could offer. The results obtained with regard to throughput (downlink and uplink) and delay (ping) for four BTSs with the 5G service are shown in Figures 14 to 16.

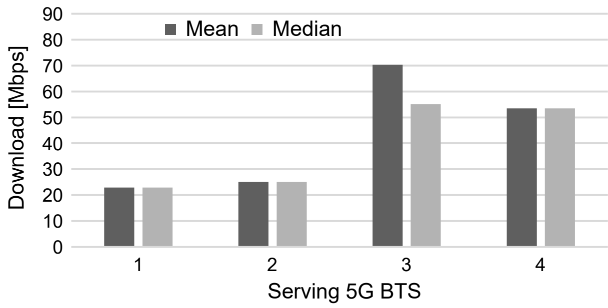

Figure 14. Download speeds of serving 5G BTSs in 2021

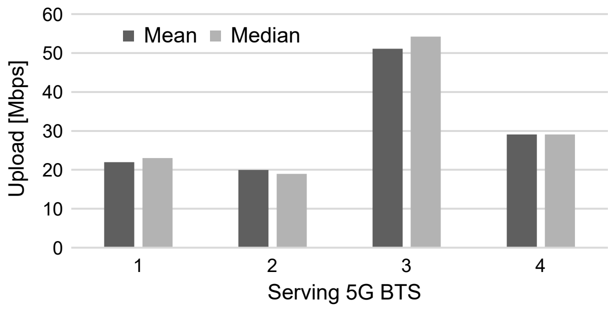

Figure 15. Upload speeds of serving 5G BTSs in 2021

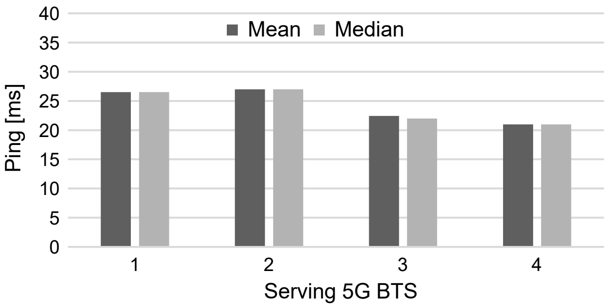

Figure 16. Ping values of serving 5G BTSs in 2021

The results of the measurements obtained in the 5G BTSs environment show similar outcomes to those of LTE-supporting BTSs (see Figures 8 to 10). This raises the question as to what extent the end-user devices were able to support the new 5G technology. Could cellular network operators, owing to the restricted use of the 5G standard, initially limit the network resources allocated to individual BTSs stations? Here, conversations with network operators might explain this pattern of behavior in the terrestrial cellular network.

Conclusions

Data from the cellular network have proved to be one of the most effective aids toward understanding large-scale human mobility for various geographically extensive computing applications because of the widespread use of smartphones and the low cost of crowdsourcing. But the creation of mobility models based on terrestrial cellular network data has been hampered by a lack of spatial-temporal studies. In an overwhelming number of cases, user locations are linked with smartphone activities, for example, calls, texts, or data transfer (Fang et al., 2021).

The exponential increase in demand for multimedia services is one reason behind the unprecedented growth of mobile data traffic. Video traffic patterns have significantly changed in recent years owing to the spread of COVID-19. The pandemic has induced many individuals to work from home and to use various online video platforms (e.g., Zoom, Clickmeeting, and MS Teams). With the introduction of the 5G mobile network, it has become imperative for mobile operators to maximize network capacity and offer different types of interfaces (Anand, Togou & Muntean, 2022a).

The results of our analysis provide a practical description of the changes that have occurred in terms of resource allocation in terrestrial mobile cellular systems. Remote learning, and the limited mobility of users associated with it, had a noticeable effect on both download and upload throughput, and a minor effect on the level of delay. In the case of a BTSs roaming environment, a reduction in download throughput is patently obvious and the ping value increases several-fold. Also, the first measurements in the 5G environment seem very interesting. They will have to be continued with a wider group of UE to obtain sufficient data to optimize the resource allocation of this type of mobile network.

Of course, the matter of designing and implementing algorithms and mechanisms for resource allocation and management, such as bandwidth, channel, or power consumption, would be an interesting field to investigate. However, in our scenario, all of them are on the MNO side and remain untouched with respect to each serving BTSs. Additionally, such investigations would have to be limited to a single network operator, not multiple ones. Nevertheless, tests like that could be carried out in the near future in cooperation with interested third parties.

Measurement results obtained in the years 2019 to 2021 show the capability of the access network under study to provide a number of multimedia services. The work has practical advantages, constituting valuable support for mobile network operators in terms of optimizing the management of available resources. It must be pointed out that the actual form of remote education is different depending on the type of classes (i.e., lectures, seminars, exercises, laboratories, or projects). Each of these demands a different level of interactivity, both for the teacher and the students. This especially arises when real-time services come into play, and even more so when two-way voice communication and video conferencing are involved, or the sharing of resources in the form of a multimedia data stream or uploaded reports. In this regard, both downlink, uplink and, of course, delay play a key role. Our previous study (Falkowski-Gilski & Uhl, 2022), performed prior to 2019, which concentrated on throughput and delay, coupled with QoS and QoE aspects of the UE, discusses a similar research campaign in an open outdoor environment.

Future research could also take a wider spectrum of user activities or selected streaming services (Biernacki & Tutschku, 2014; Nightingale et al., 2018; Falkowski-Gilski & Uhl, 2020; Biernacki, 2022) into account as well. The measurements in the recently launched 5G networks should also be continued (Cheng, Li & Zhou, 2021; Balmuri et al., 2022; Mongay Batalla et al., 2022) and must incorporate an analysis of a broader range of user activities

(Gutierrez et al., 2022) and usability aspects (Weichbroth, 2022). It would also be interesting to analyze a broader range of UE (Falkowski-Gilski, 2020; Rybka et al., 2022), with a particular emphasis on the energy efficiency aspect (Cichoń, Kliks & Bogucka, 2016), not to mention the pre- and post-pandemic scenario (Pal, Vanijja & Patra, 2020; Tang et al., 2021). Another aspect is the proper handling of data packets, coupled with a review of rebuffering and queueing mechanisms (Mongay Batalla et al., 2016; Chydziński & Samociuk, 2019; Barczyk & Chydziński, 2022) or the file sharing and cloud-based services (Perumal et al., 2022; Ramachandra et al., 2022).

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