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Evaluating Quality of Experience of Upstream Video in 5G Networks

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of the requirements for the degree of
MAI (Computer Engineering)

Declaration

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Abstract

5G has become a reality and as mobile carriers begin to roll-out their 5G infrastructure, academics are exploring 5G-like network simulations to learn more about what the future generation of mobile networking will look like. The available bandwidth provided to users around the world continues to grow and this has seen a rise in both network traffic and a rise in new kinds of services and applications. The last few years have seen a huge growth year-on-year in upstream video traffic with services such as Facebook Live, YouTube Livestreaming and Twitch.tv gaining popularity.

This work describes the design and implementation of a 5G end-to-end network simulation which simulates the transmission of video upstream from a mobile device to a remote host. The simulation was designed using the discrete event network simulator ns-3 and the 5G end-to-end network was implemented using a combination of the mmWave ns-3 module developed by NYU and the Evalvid ns-3 module developed by Gercom. A Quality of Experience framework was then set up at the remote host to evaluate the performance of the network in a range of experimental scenarios. This framework was centered on the use of the Video Quality Metric General Model developed by the NTIA.

The findings of this dissertation illustrate the potential that 5G has to offer in providing exceptional performance that will undoubtedly enable high-quality upstream video transfer. The findings also show some limitations of 5G mmWave networks including a sharp reduction in performance as users move into Non-Line-of-Sight conditions caused by obstacles and buildings. This means a high densification of 5G infrastructure will inevitably be required in Urban areas to guarantee high quality coverage. Finally, this work shows that MAC layers techniques such as Hybrid Automatic Repeat Request will be vital for sending video upstream in mmWave networks as it can help mitigate against packet loss due to rapid variations in channel quality.

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I'd like to thank my academic supervisor, Meriel Huggard, for her time and advice over the last few months. She was always available when I needed guidance and our conversations were valuable and motivating.

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1 Introduction

The fifth generation of mobile networking promises not only to offer new applications and services, but to greatly enhance the level of services already provided in current mobile networks. 5G networks lie at the cutting edge of network simulation research. This dissertation describes the design of a system that simulates upstream video transmission, i.e. from a mobile device to a remote host, in a 5G network. The Quality of Experience for the user at the remote host is then evaluated. 'Quality of Experience' is a metric used to represent the perceived quality of a video by an average user. This system allows us to gain insight into the Quality of Experience 5G networks can provide when up-streaming video in a range of experimental scenarios.

1.1 Motivation

5G is no longer the future, it is now a reality. 2020 heralds a new dawn in mobile communications and the commercial deployment of 5G systems has already begun in countries such as Japan, the United Kingdom and the United States. 5G is expected to be widely adopted by 2025 (1). 5G arrives as mobile communication usage continues to grow. In 2020, monthly global mobile data traffic is expected to be 30.6 exabytes (8).

As the performance of current generation mobile systems has improved over the last few years, the services these systems provide continue to expand. Thanks to advancements in upstream bandwidth, more services which utilise upstream video traffic are not only available but are rapidly growing. This growth is especially noticeable in the livestreaming industry with platforms such as Instagram, Facebook and YouTube all providing live upstream video services, allowing its users to share their experiences live with their audience. A 2020 report from Sandvine reveals that 22.4% of mobile upstream traffic is video streaming (9).

More recently, the sharp increase in people working from home due to COVID-19 has driven a rise in the use of video conference platforms like Skype and Zoom. It is likely that in this new reality, there is more video being sent upstream than ever before in the history of the internet.

The quality of the network when sending upstream traffic is particularly important given that in most applications the traffic is processed and then forwarded downstream to another user to be consumed. This is not the case with normal downstream video applications such as YouTube where the high quality content is already stored at the remote host and the quality for the eventual consumer solely relies on their connection between their device and the remote host.

Providing upstream video to the remote host which arrives with an excellent Quality of Experience means you are winning half the battle and the video can then only be impaired by the downstream connection to the eventual consumer.

There is also a potential for 5G technologies to be used in other industries that rely on upstream video streaming such as the television industry. In 2019, AT&T published a case study on their experience using 5G networking technologies at the U.S Open (10). Research in this area may be particularly useful given the cost benefits of implementing 5G infrastructure at sporting events such as the U.S Open, where the alternative involves deploying fibre cables the full length of the golf course.

Despite the amount of research in the area of 5G and also the rise in upstream video communications, I was unable to find a body of research which implements upstream video traffic in a 5G end-to-end network simulation. The implementations of 5G networks in network simulators are still in their infancy and this area of research is still growing. This gap in research is an opportunity for this work to provide insight that is currently not available.

1.2 Research Objectives

The main objective of this research is to design a 5G end-to-end network simulation that can simulate upstream video traffic and then evaluate the Quality of Experience for the user at the remote host.

The implementation of this 5G end-to-end network should be both accurate in its conformity with standards outlined by the relevant standards bodies and also reliable in its function. The Quality of Experience evaluation should give us metrics that allow us to accurately compare and contrast the performance of many different network scenarios contained within this research.

The upstream video traffic should be an accurate reflection not only of today's main stream video traffic but the also the video traffic of the future. This may involve research using high quality video technologies such as 4K resolution and high frame rates.

1.3 Dissertation Structure

Chapter 2 describes the necessary background information and related research in the area of 5G and Quality of Experience.

Chapter 3 will outline the design and implementation of the 5G end-to-end network simulation. It will also describe the full experimental process used to obtain results.

Chapter 4 outlines the results obtained for a number of experimental scenarios and evaluates these results.

Finally, Chapter 5 will conclude this dissertation and suggest any future avenues for research.

2 Background

2.1 5G Overview

5G is the fifth generation of cellular mobile communications. Previous generations include 4G (LTE-A/ WiMAX), 3G (UMTS) and 2G (GMS) (11). Compared to its previous generations, 5G promises to offer new applications and services through seamless coverage, high data rate, low latency, significantly improved performance and reliable communications (11). Widespread adoption of 5G networks is anticipated by 2025 (1).

International Telecommunication Union (ITU) and other organisations such as the 3rd Generation Partnership Project (3GPP) are developing 5G standards as well as the use cases of 5G (11).

These organisations envisage various types of use cases and wireless services ranging from high speed links with peak data rates of 10 to 20 Gbps to lower speed links with extremely low latency and high connection density (1 mn/Km2) for Internet of Things devices.

ITU defined the requirements for 5G in its 'IMT-2020' specification. The standards body 3GPP, who have been at the forefront of developing mobile technology standards for the last 25 years, are now developing standards based on the 5G requirements as outlined in the 'IMT-2020' specification.

2.1.1 Capabilities

To give you a sense of 5G and its capabilities, ITU considers the following parameters as key capabilities of 'IMT-2020':

(1) **Peak data rate:** The maximum achievable data rate under ideal conditions per user/device in Gbps. For the enhanced Mobile Broadband (eMBB) use case, the peak data rate is expected to reach 10Gbps in the upstream direction. In the downstream direction, it could support a peak data rate of 20Gbps (12). For context, the peak downstream data rate of 4G (LTE) is approximately 100Mbps (13).

(2) **User experienced data rate:** The achievable data rate across the coverage area to a mobile user/device. IMT-2020 outlines different achievable data rates depending on the scenario. For example, for wide area coverage cases such as rural and suburban areas, the achievable data rate would be around 100Mbps, while in urban hotspots where the coverage area is smaller, the achievable data rate is expected to be around 1Gbps (12).

(3) **Latency:** The time from when a source sends a packet to when the destination receives it (in ms). IMT-2020 specifies support for 1ms over-the-air latency in Ultra-reliable Low-Latency Communication (URLLC) use cases and 4ms in eMBB use cases. (12), This is compared with around 5ms over-the-air latency in previous generation 4G (LTE) networks (13).

(4) **Connection density:** The total number of connected and/or accessible devices per unit area (per km^2). IMT-2020 specifies that the supported connection density is expected to be up to $10^6/km^2$ in use cases such as Massive Machine Type Communication (12).

Figure 2.1 shows the comparison between 4G and 5G on a number of key networking performance metrics.

Figure 2.1: 4G vs 5G Capabilities. Source: (1)

Performance Metrics	4G	5G
Peak data rate (Gbps)	1	20
User experienced data rate (Mbps)	10	100
Connection density (devices/km^2)	10^5	10^6
Mobility support (kmph)	350	500
Area traffic capacity (Mbit/s/m^2)	0.1	10
Latency (ms)	10	1
Reliability (%)	99	99.99
Positioning accuracy (m)	1	0.01
Spectral efficiency (bps/Hz)	3	10
Network energy efficiency (J/bit)[1]	1	0.01

2.1.2 5G Technological Enablers

In order to meet these requirements of 5G, the next generation of networking will require some new technological enablers to make it a reality. The research community has identified three key enablers for ensuring the requirements are met:

(1) Large quantities of new bandwidth (mmWave)

(2) Many more antennas (MIMO)

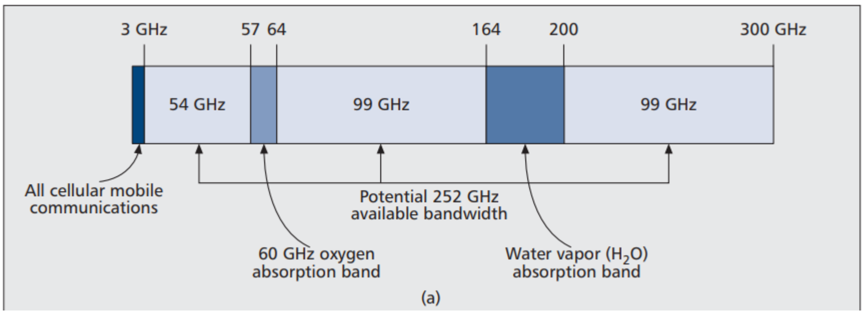
(3) Extreme densification of infrastructure

With the high available bandwidth requirements as outlined in the previous section, more spectrum bandwidth will be required to deploy 5G.

Previous to 5G, almost all mobile communication systems used spectrum in the range of 300 MHz–3 GHz. This narrow-band of spectrum has generally been considered the sweet-spot given its favourable propagation characteristics. But as both the number of users and the amount of data required by applications and services grows, the sub-3 GHz spectrum has become increasingly crowded (2).

As outlined in Figure 2.2 after removing both the oxygen absorption band (57-64 GHz) and the water vapour absorption band (164-200 GHz) there is potentially 252 GHz of spectrum suitable for mobile broadband within the 3–300 GHz spectrum.

Figure 2.2: Available mobile spectrum 3-300 GHz. Source: (2)



The oxygen absorption band of 57-64 GHz refers to the worse attenuation experienced there of around 15 dB/hm due to the oxygen molecule (O2) which absorbs electromagnetic energy at around 60 GHz.

mmWave is well known anecdotally for its poor propagation characteristics. There is also a misconception, even among engineers, that higher frequencies have worse propagation than lower frequencies in free space.

This misconception has its roots in engineering text books where it is frequently stated that lower frequencies use antenna which are surrounded with a larger aperture resulting in larger gain as it captures more energy from a passing radio wave. Similarly, smaller antenna are generally surrounded by smaller aperture.

However with shorter wavelengths, as the size of the antenna decreases more antennas can be packed into the same large aperture area. With the same antenna aperture area, higher frequencies should not have any inherent disadvantage compared to lower frequencies in terms of free space loss (14).

The poor propagation characteristics that mmWave is known for lies in its large attenuation following penetration of most solid materials. Most solid materials, including foliage, will cause mmWave signals to reflect or diffract, but in some cases this reflection and diffraction does help facilitate Non-Line-of-Site (NLOS) communication as the wave is steered around obstacles to the eventual user.

The high levels of attenuation of mmWave signals due to building materials such as brick and concrete may confine the coverage area of outdoor mmWave base-stations to streets and open street canyons. mmWave has even been shown to experience high levels of attenuation in the presence of heavy rain (2).

To meet the requirements of 5G, it's clear that the real-world deployment scenarios will have to use a variety of different spectrum frequencies. For example, low latency and short range use cases (i.e. urban areas) will use mmWave frequency while long range and lower-bandwidth use cases (rural areas) will use sub 7GHz frequencies.

In an urban scenario where you are using mmWave frequency, you will require a shorter distance between mmWave radio nodes to compensate for the larger levels of attenuation. For example, in the the European Telecommunications Standards Institute (ETSI) technical report "Study on channel model for frequency spectrum above 6 GHz" (6) which models propagation channels above 6GHz in multiple scenarios, they recommend an intersite distance (the distance between radio nodes) of 500m in Urban Macro scenarios. This will require a far higher densification of mobile networking infrastructure than was required in previous generations.

2.1.3 Use Cases

The use cases of 5G will support a large variety of applications given the substantial capabilities of the cellular generation relating to mobility, data speed, latency and reliability.

The 5G use cases can be categorized into three different categories (15):

(1) Enhanced Mobile Broadband (eMBB): This use case delivers gigabytes of bandwidth on demand.

(2) Massive Machine-Type Communication (mMTC): This use case connects billions of machines.

(3) Ultra Reliable and Low-Latency (URLL) communication: This use case allows for immediate feedback with high reliability for critical services.

This dissertation focuses on the eMBB use case which provides gigabytes of bandwidth on demand and can support high bit-rate applications such as high quality media streaming.

2.2 Upstream vs Downstream Traffic in Mobile Networks

Downstream traffic has always been prioritised over upstream traffic. This is simply due to the higher proportion of applications and services which require mostly downstream traffic. The majority of what people use their devices for is to receive information or media. A 2020 report released by the Sandvine reveals that 65% of all mobile downstream traffic is video streaming (9).

In LTE networks, the highest theoretical bandwidth available to users in the downstream direction is 300 Mbps while in the upstream it's only 75Mbps. This is because in LTE networks, even though both upstream and downstream links use a maximum of 20MHz of bandwidth, the downstream link uses spatial multiplexing which offers additional data capacity by increasing the number of 20MHz bandwidth shares the user can access (16). This means that applications and services that utilise upstream bandwidth are starved of resources in comparison to their downstream counterparts.

While it has always been true that downstream traffic dominates the internet, it is also the case that upstream traffic, and specifically upstream video traffic has been growing rapidly with the rise in platforms which allow for live video streaming such as YouTube and Twitch. The same Sandvine 2020 report reveals that 22.4% of upstream traffic is video streaming (9).

It is now likely that following the public health measures issued by authorities globally due to COVID-19, the sharp increase in usage of platforms like Skype, Zoom and Google Hangouts means that more video is being sent upstream than ever before in the history of the internet. In turn, users may also be feeling the affects of congested networks more than ever before which is compounded by their limited upstream bandwidths.

2.3 Quality of Experience Overview

Quality of Experience (QoE) is defined as; "The overall acceptability of an application or service, as perceived subjectively by the end-user" (17). The key word in the definition being 'subjectively', highlighting that the metric is only concerned with the specific users perception and not any overall technical performance indicators.

In spite of this, QoE can be measured both subjectively and objectively. A subjective score could be obtained by using user surveys, for example asking the user to rate the experience of the service using a scale such as Mean Opinion Score (MOS). Mean Opinion Score is an ITU standardized 5-point scale where 5 is the highest rating indicating excellent quality while 1 is the lowest rating indicating bad quality (18). An example of MOS being used is the user survey after a Skype call asking the user to rate the quality of their call on a scale of 1 star to 5 stars. This scale has often been used in QoE research, but the method of obtaining it via user surveys and through research groups is time consuming.

Alternatively, lots of work has been done in the area of estimating objective scores for QoE, that is obtaining an objective score that would reliably correlate with a subjectively obtained QoE score. While objective evaluations may not be as accurate given that they are essentially predictions, the objective evaluation allows us to obtains scores which are more predictable and more importantly allow us to run evaluations in real-time as the user is using the service. This is very important for the potential development of adaptive systems that can react to these QoE scores and try to improve performance for the user in real-time.

2.3.1 Objective Video QoE Assessment

Objective video QoE assessment is used to obtain an objective score of the perceived quality of experience that reliably correlates to the QoE score if the score was obtained subjectively using a human evaluation. The main benefit of these assessments is that it allows us to predict the perceived video quality without human intervention.

To accomplish this, most video quality assessment metrics require information about the reference video (the original unimpaired video). The amount of information required allows us to classify video quality assessment metrics into three types.

Full Reference: Full reference metrics require the entire reference video to be available in unimpaired form (19). They perform a frame by frame comparison of the reference and the test video.

An example of a well known objective QoE method that uses full reference evaluation is Peak Signal to Noise Ratio (PSNR). PSNR is calculated by comparing the peak noise (in dB) of every frame from the reference video to the test video. The average PSNR score is then obtained by averaging the PSNR score from every frame.

The score has also been mapped to MOS through the ITU-T J.144 standardized formula (20). But as noted in "Using Machine Learning to Predict Quality of Experience of Video in LTE Networks" (21), it has been widely accepted in research that PSNR does not accurately reflect subjective QoE scores as it only compares aspects of the original video to the transmitted video and does not take into account any aspects of human perception (22, 23).

No-Reference: No reference metrics analyse only the test video and do not require any information about the reference video. These are more suitable for real-time evaluation and can be used where the reference video may be unavailable (or does not exist) (19).

An example of a no-reference metric is the blockiness estimation. It is based on the blocking artifact which is a prevailing degradation caused by the block-based Discrete Cosine Transform (BDCT) coding technique under low bit-rate conditions. BDCT is used by many image/video coding methods (e.g.,JPEG, MPEG) (24).

A lot of work has gone into developing algorithms that detect and measure the blockiness artifacts in BDCT coded images (25, 26), but given that this research does not require real-time evaluation, it was decided to research more accurate methods of QoE assessment.

Reduced Reference: Reduced Reference metrics extract a number of features from the reference video (e.g. the amount of motion or spatial details) and uses only those features to make a comparison between the reference and test video (19). It is somewhat of a compromise between Full Reference and No-Reference metrics.

An example of a Reduced Reference metric is Video Quality Metric (VQM). Developed by the National Telecommunications and Information Administration (NTIA), it has been shown to produce excellent results, for example in the VQEG FR-TV Phase II tests (27). It was adopted both by the American National Standards Institute (ANSI) in July 2003 (ANSI T1.801.03-2003) as a national standard and by International Telecommunication Union Recommendations (ITU-T J.144 and ITU-R BT.1683, both adopted in 2004) (18).

The VQM calculation involves extracting a number of perception-based features, computing seven video quality parameters and combining these parameters to construct the overall model (19). The VQM software is distributed by the NTIA and is available on their website. The NTIA General Model was the only video quality estimator that was in the top performing group for both the 525-line and 625-line video tests when evaluated by the Video Quality Experts Group (VQEG) in their Phase II Full Reference Television (FR-TV) test (3). The General Model was designed to be a general purpose video quality model for a very wide range of quality and bit rates (3).

Following the success of the NTIA General Model, in 2014 NTIA announced the VQM Variable Frame Delay model (28). The new model showed improvements in predicting objective scores that correlated to subjective scores made by human subjects.

2.3.2 VQM General Model

There are 4 key steps involved in estimating QoE using the General Model (21):

(1) Reduced-reference calibration of the reference and test video is performed. This involves detecting the valid region of the video by ignoring any borders or non-picture areas that might effect the quality of the estimation. The spatial alignment process is also performed which determines the horizontal and vertical spatial shift of the processed

video relative to the original video (3). Finally, gain and level offset is calculated and temporal alignment is performed.

(2) The relevant quality features are then extracted by enhancing particular properties of perceived quality of the reference and test video. This is done using perceptual filters. Examples of these features would be noise, unnatural motion and jerkiness, blurring, blocking and colour distortion (21).

(3) The extracted features are then compared between the reference and test video. The General Model extracts seven features in total to compare.

(4) The VQM score is then calculated, Figure 2.3 shows the calculation where si_loss represents a decrease or loss of spatial information, hv_loss represents a shift of edges from horizontal and vertical orientation to diagonal orientation, hv_gaint represents a shift of edges from diagonal to horizontal and vertical, chroma_spread represents changes in the spread of the distribution of two-dimensional color samples, si_gain represents improvements to quality that result from edge sharpening or enhancements, ct_ati_gain represents moving-edge impairments such as edge noise and finally chroma_extreme represents severe localized color impairments. A VQM score of 0 indicates no impairment while a score of >1 indicates maximum impairment.

Figure 2.3: General Model VQM Calculation. Source: (3)

$$
\begin{aligned}
\mathrm{VQM} = & -0.2097 * \textbf{si\_loss} \\
& + 0.5969 * \textbf{hv\_loss} \\
& + 0.2483 * \textbf{hv\_gaint} \\
& + 0.0192 * \textbf{chroma\_spread} \\
& - 2.3416 * \textbf{si\_gain} \\
& + 0.0431 * \textbf{ct\_ati\_gain} \\
& + 0.0076 * \textbf{chroma\_extreme}
\end{aligned}
$$

2.4 Video and QoE in 5G Literature

5G is still a relatively new area of research given that the technical documents and standards for 5G have only been developed and published very recently by bodies such as ITU and 3GPP. The majority of video research that has been published in 5G literature looks at streaming in the downstream direction, that is from a remote host to a mobile device.

Important work was conducted by Hou, Zhou, Song and Gao in their 2017 paper titled "A QoE Estimation Model for Video Streaming over 5G Millimeter Wave Network" (29). The work shows that it is possible with current mainstream network simulators to create a 5G end-to-end network and simulate video traffic, but this video traffic was sent in the downstream direction where they evaluated the QoE at the mobile device. The work also uses PSNR to evaluate QoE but it has been shown in research that PSNR does not accurately reflect subjective QoE scores (22, 23).

Despite this, the work does use a popular network simulator in academia called ns-3. It implements a 5G end-to-end network using a mmWave module developed by New York University. It then simulates video traffic using a ns-3 module called Evalvid. This work was very useful and further considered in later chapters.

Work published by Tikhvinskiy and Bochechka in 2015 titled "Prospects and QoS requirements in 5G networks" (30), outlines the prospects and requirements for some Key Performance Indicators that determine the Quality of Service (QoS) for video in 5G networks. The requirements they propose are specifically based on the analysis of functional requirements for 5G networks and traffic parameters for HD video. They claim that high quality video services such as HD and 4K UHD video will be the dominant service in 5G networks. They state that spectrum bandwidth of 500 to 1000 MHz in both the downstream and upstream direction will be necessary to meet the requirements of future 5G networks. This is massive in comparison to the typically 20MHz which is currently allocated to users in the upstream direction in current LTE networks (16).

In 2015, Pierucci published a paper titled: "The quality of experience perspective toward 5G technology" (31). In the paper, Pierucci highlights the key innovations of 5G technology and how they might impact (positively or negatively) Quality of Experience. These innovations include heterogeneous networks, mmWave and native support of D2D/M2M which involves the sharing of information between neighboring devices.

Pierucci proposes the use of Neural Network techniques as an efficient technique for adaptive estimation and self-optimization of the quality perceived by the user (31). This process involves the neural network mapping/correlating important Quality of Service parameters to a users Quality of Experience.

Pierucci concludes that using Neural Networks is a convincing proposal for an adaptive estimation and automatic classification of the quality perceived by the user in 5G systems as it both not subjective (such as user submitted MOS) and during tests on real Key Performance Indicators collected from the HSPA network of TIM (Telecom Italian Mobile), the neural network only failed to properly classify about 1 percent of the total data (31).

Following the paper published by Peirucci in 2015, in late 2019 Schwarzmann, Cassales Marquezan, Bosk, Liu, Trivisonno and Zinner published a paper titled "Estimating Video Streaming QoE in the 5G Architecture Using Machine Learning" (32). They used the Omnet++ Simulation Environment to simulate their 5G network and their simulation sent video from a server downstream to the mobile device. Their experiments were performed with between 20-200 stationary devices requesting video. Their system collected Quality of Service parameters during transmission which were the features for their machine learning models.

They chose not to use Neural Networks and instead chose to use a Linear Regression model and a Support Vector Regression model. They showed that subjective QoE scores could be reliably estimated using solely standard regression approaches (32). They also found that only a small number of features were required for obtaining sensible accuracy. Despite these findings, they conceded that given the simulation-based nature of their experiment, their findings would still need to be verified in a real world deployment.

In 2018, Nightingale, Salva-Garcia, Calero and Wang published a paper titled "5G-QoE: QoE Modelling for Ultra-HD Video Streaming in 5G Networks" (33). The purpose of the work was to develop a QoE prediction model that was both sufficiently accurate and of low enough complexity to be employed as a continuous real-time indicator of the "health" of video application flows in 5G networks (33). Their model was created using a 5G network monitoring layer which inspects and extracts metrics from the 5G mobile edge network. This data is then stored in a database and is used to inform decisions in the network management system.

To build the QoE model they used the Congestion Index (CI), which is a measure of the ability of the network to successfully deliver a real time video stream based on the minimum available bandwidth on the path from sender to receiver (33). CI can be calculated using the ratio of the maximum required bandwidth for the video stream divided by the available bandwidth for the video stream (33). They used a subjective data set obtained from human subjects to map CI to MOS using regression and curve fitting.

They then evaluated the performance of the QoE model by comparing the predicted values obtained by the model with the results obtained in another subjective evaluation data set. This showed that the model had an accuracy of up to 94%. They concluded that future work will involve building an adaptive system that leverages the QoE model generated in their work and which can analyse and optimise the QoE for users in future 5G networks.

There has also been research into video transmission using specific 5G technologies such as mmWave. This research has demonstrated the massive available bandwidth at mmWave frequencies. For example in the paper titled "A 60 GHz Wireless Network for Enabling Uncompressed Video Communication", researchers showed that the 60 GHz band could be used to transmit uncompressed, high quality video up to 3 Gbit/s (34). Also, in the paper "Enabling high-quality untethered virtual reality", the researcher uses mmWave to handle multi-Gbps VR communication from a local server to a headset (35).

I was unable to find any research that simulated upstream video traffic in an end-to-end 5G network and then evaluated the QoE at the remote host.

3 Design and Implementation

3.1 Design Process Overview

(1) Understand ns3

(2) Research implementations of 5G network elements in ns-3

(3) Design the end-to-end network simulation

(4) Research and implement upstream video traffic in the simulation

(5) Obtain QoE measurements

3.2 ns-3 Overview

Released in 2008, ns-3 is a discrete-event network simulator. It is widely used in both academic research and teaching. ns-3, an open source platform, is the third distribution of the network simulator following the first two distributions; ns-2 and ns-1.

ns-3 is written in C++ and supports Linux based systems. The simulator consists of modules which allow you to accurately simulate network elements. Each module consists of models of core network elements such as Network Nodes, Network Devices, Communication Channels and Communication Protocols (21). Complete documentation is available on the ns-3 website which details how to install ns–3, set up ns–3 scenarios and topologies, handle the collection of statistics and log useful messages (4).

The simulator is distributed as a package of folders. One such folder, the src folder, contains all of the modules. Each module contains models of network elements, examples on how to use and link the elements in C++, tests and further documentation.

The main distribution of ns-3 comes with a basic set of modules including modules for mobility, buildings, LTE, WiFi and many more. These modules can be aggregated to create detailed and varied network scenarios to perform cross-layer design and analysis. Modules are often designed in academia by research institutes and shared online for others to include in their own ns-3 simulations. In some cases these modules will make it into the main distribution on ns-3.

In the case of 5G network elements such as mmWave nodes, there is no module that comes with the main distribution of ns-3 that is designed to accurately simulate these 5G network elements. This meant that I was required to research implementations of 5G components in ns-3 which have been designed in academia.

3.3 Implementations of 5G End-to-End Networks in ns-3

3.3.1 NYU mmWave

The first ns-3 module I found which models 5G network elements was the mmWave module developed by NYU Wireless, centered at New York University Tandon School of Engineering. It has been used in previous 5G works, such as when it was used to simulate video traffic downstream in a 5G end-to-end network (29). Its architecture builds upon the ns–3 LENA LTE module, a very popular LTE module which is distributed with the main ns-3 distribution. The mmWave module version 2.0 was released in 2018. The module was designed to perform end-to-end simulation of 3GPP-style cellular networks as described in their 2018 paper "End-to-End Simulation of 5G mmWave Networks" (4). mmWave stands at the forefront of the development of 5G networks, as its high frequency range; 24-100 Ghz, allows for the extremely high throughput which will be required by future 5G networks (2).

Figure 3.1: NYU 5G End-to-End Topology. Source: (4)

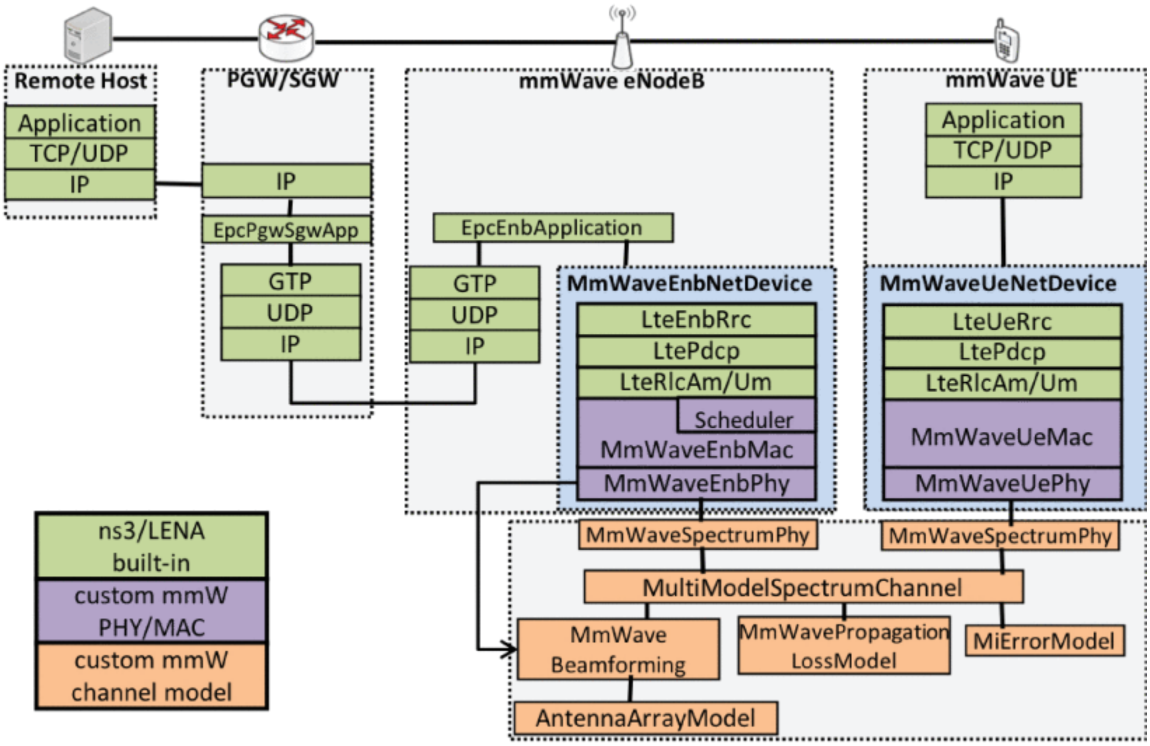


Figure 3.1 shows the composition of the MmWaveEnbNetDevice and MmWaveUeNetDevice classes, which represent the mmWave eNodeB (eNB) and User Equipment (UE) radio stacks in ns-3. It also shows a standard end-to-end cellular network topology representing the whole link from the remote host to the UE. This is the exact topology of the network we are looking to design.

The module also includes a McUeNetDevice, which is a NetDevice with a dual stack LTE and mmWave meaning it can connect using both technologies. This would be useful for modelling scenarios where the UE switches between the two technologies as they move in the environment which will be a common occurrence in the real world until a large amount of 5G infrastructure is deployed.

The module comes with a choice of three 5G channel models which support carrier frequencies ranging from 6-100 GHz. The most flexible and detailed channel model is based on the work outlined by 3GPP in a 2017 study on channel modelling in the 6-100 GHz range, the findings of which were outlined in the following European Telecommunications Standards Institute (ETSI) technical report (6).

NYU also describe various simulation scenarios in their 2018 paper and outline the process for creating accurate end-to-end simulations of 5G networks.

3.3.2 5G LENA

The 5G LENA module was created by the Mobile Networks Group of the public research institute; Centre Tecnològic de Telecomunicacions de Catalunya. The latest version, v0.3, was released in August 2019. They outline their implementation of 5G end-to-end networks in the paper "An E2E Simulator for 5G NR Networks" (36).

The team were also responsible for the very popular ns-3 module LTE LENA which NYU's mmWave module's architecture was built on (4).

The 5G LENA module was generated from the previous LTE LENA module and the NYU mmWave module. It uses the same 3GPP channel models that are also available in the NYU mmWave implementation, based on the 2017 3GPP channel modelling study (6).

While the NYU mmWave module implements both features derived from their own studies (such as their NYU channel model) and features from 3GPP technical papers, the 5G LENA module exists to primarily focus on conforming to 3GPP 5G New Radio standards outlined in technical papers such as in (37) and (38).

I initially decided to work with this module given both the notoriety of LENA in the ns-3 simulation industry and their strong conformity with 3GPP standards and findings, but I found that unfortunately the module was still in its early days of development.

Not having reached version 1.0 yet, it was clear that there was still some teething issues to be worked through. After a week debugging compilation issues, I decided that it was inefficient to be continuously debugging problems when I could instead use the tried and tested NYU mmWave module which was far more developed.

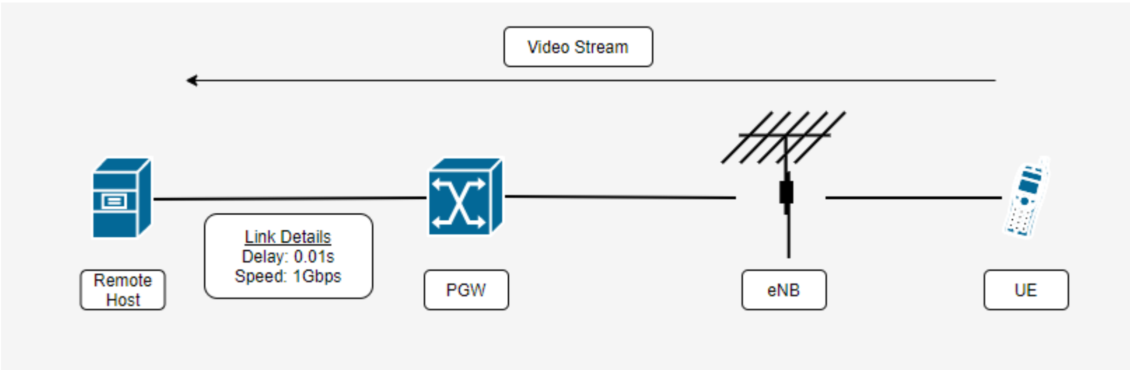
3.4 Designing the 5G Simulation

Having chosen the NYU mmWave module, it was time to start designing the simulation which began with creating the network topology.

3.4.1 Network Topology

The initial phase of designing the network topology as shown in Figure 3.2 was aided by examples provided with the mmWave module package. The simulation was written entirely in C++.

Figure 3.2: My End-to-End Network Topology



Firstly, the UE, the eNodeB (eNB, which represents the radio tower) and the remote host are all instantiated. The next item to setup is the MmWaveHelper object, which provides methods to create the entities involved in the simulation (e.g., the channel-related objects and the physcial and mac layer objects) (4).

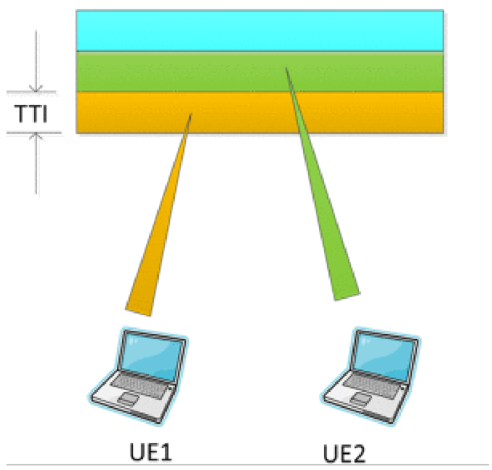
The mmWave stack is then installed over the UE and the eNB, and the initial attachment of a UE to the closest eNB is performed.

The core network and the Internet are then set up. This is done by using the MmWavePointToPointEpcHelper which provides a pointer to the Packet Gateway (PGW) node. The PGW is then connected to the remote host and the eNB. Finally the Internet stack (i.e. the IP protocol suite) is added to the UE and the remote host.

While having only one UE is an unrealistic scenario, this does not mean that the UE will gain any advantage in terms of bandwidth. The NYU module implements a Time Division Multiple Access (TDMA) MAC scheme. TDMA is a channel access method that allows several users to share the same frequency band. Using TDMA and a scheduler, each user is assigned the same bandwidth and that bandwidth is allocated to them on the time domain as shown in Figure 3.3 where TTI is one Transmission Time Interval.

While only having one UE means there will not be any problems with scheduling the user their bandwidth allocation, you would have to instantiate a very large number of devices to start seeing any effects due to scheduling issues. This is simply not feasible due to the computational complexity of running such a simulation. Even adding two to three more UEs to the simulation causes a very noticeable increase in simulation run time and there is not much benefit to doing so as there would not be any noticeable reduction in performance for any of the UEs.

Figure 3.3: TDMA Scheduling. Source: (5)



3.4.2 The Channel Model

In the paper 'End to End Simulation of 5G mmWave Networks' (4), it is stated that one of the most important elements that needs to be considered when designing a mmWave cellular simulation is the channel model. The term 'channel' refers to the medium between the transmitting antenna and the receiving antenna. The channel model is a fundamental component of every wireless simulation. The channel is one the main elements that affects the end-to-end network performance.

The characteristics of a wireless signal changes as the signal propagates from the eNB to the UE. This change can be caused by the distance between the the eNB and the UE, the path taken by the signal, and the environment (buildings or other objects) (7). We can calculate the difference between the transmitted signal from one antenna and the received signal at the other if we have a model of the medium that the signal passes through. The model of this medium is known as the channel model.

The NYU mmWave module was distributed with three channel models to choose from when designing your simulation.

3GPP Statistical Channel Model

The 3GPP Statistical Channel Model is based on the official 3GPP channel models, outlined in the ETSI technical report 138 900 V14.2.0 (6), which were published to be used as a standard in network simulators. The models focus on the 6-100GHz band of cellular frequency. The generation of the models was based on measurement campaigns of propagation at mmWave frequencies conducted by several 3GPP partners (39). The study describes channel models based on different scenarios which outline several cellular network deployments including Urban Macrocells, Urban Microcells and Rural scenarios:

(1) **Rural Macro:** Focuses on larger and continuous coverage in rural areas (6-7 GHz range).

(2) **Urban Macro:** Focuses on shorter coverage in urban areas (24-100 GHz range).

(3) **Urban Micro-StreetCanyon:** Focuses on shorter coverage in urban areas where the eNB is located on top of a building looking down into a open street square (24-100 GHz range).

Depending on the chosen scenario, the study specifies the path loss model in both Line of Sight (LOS) and Non Line of Sight (NLOS) conditions. Path loss is the signal loss due to energy dissipation as the energy is spread spherically around the transmitting antenna (7). The path loss model returns the path loss in dB between the eNB and the UE. The path loss for both LOS and NLOS is a function of distance, frequency and in some cases, height of the eNB and UE.

Figure 3.4 shows the path loss model for the Urban Macro scenario (UMa).

It specifies different path loss models depending on if the UE is in LOS and NLOS conditions with the eNB. In the case of LOS, it also specifies two different path loss models depending on the 3D distance between the eNB and the UE. On the right hand side of the table, it shows the applicability range for the models, for example, in the case of LOS, h_{UT} which denotes the height of the mobile user must be between 1.5 meters and 22.5 meters. Similarly the h_{BS}, which denotes the height of the base station (eNB), must be 25m exactly.

Figure 3.4: UMa Channel Model. Source: (6)

UMa	LOS	$PL_{\text{UMa-LOS}} = \begin{cases} PL_1 & 10\text{m} \le d_{2D} \le d'_{BP} \\ PL_2 & d'_{BP} \le d_{2D} \le 5\text{km} \end{cases}$, see note 1 $PL_1 = 32.4 + 20\log_{10}(d_{3D}) + 20\log_{10}(f_c)$ $PL_2 = 32.4 + 40\log_{10}(d_{3D}) + 20\log_{10}(f_c) - 10\log_{10}((d'_{BP})^2 + (h_{BS} - h_{UT})^2)$	$\sigma_{SF} = 4$	$1.5\text{m} \le h_{UT} \le 22.5\text{m}$ $h_{BS} = 25\text{m}$
	NLOS	$PL_{\text{UMa-NLOS}} = \max(PL_{\text{UMa-LOS}}, PL'_{\text{UMa-NLOS}})$ for $10\text{m} \le d_{2D} \le 5\text{km}$ $PL'_{\text{UMa-NLOS}} = 13.54 + 39.08\log_{10}(d_{3D}) + 20\log_{10}(f_c) - 0.6(h_{UT} - 1.5)$	$\sigma_{SF} = 6$	$1.5\text{m} \le h_{UT} \le 22.5\text{m}$ $h_{BS} = 25\text{m}$ Explanations: see note 3

Path loss is not the only component of the channel model, there is also shadowing and multi-path components.

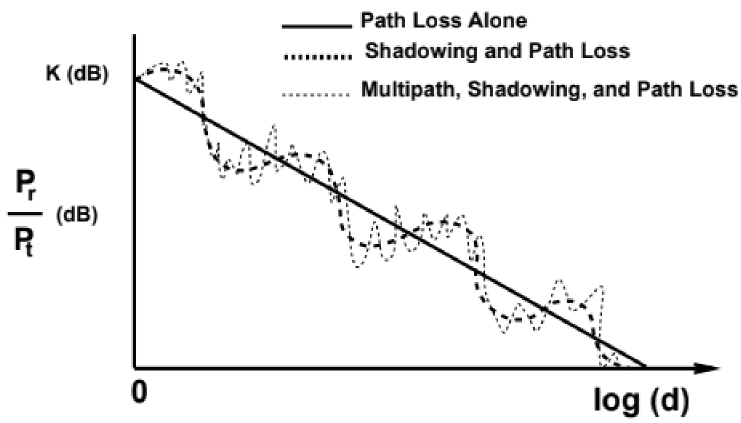
Shadowing is the loss of signal due to blockage (objects or buildings) along the path of the signal. It accounts for signal loss through absorption, reflection, scattering, and diffraction (7). Shadowing is a normally (Gaussian) distributed random variable (in dB) with standard deviation σ.

This standard deviation is also declared as part of the 3GPP channel model. It can be seen in Figure 3.4, denoted as σ_{SF}.

Multi-path refers to the reflections/deflections caused by the objects located around the path of the signal. Some of these reflections/deflections can still reach the receiver (7).

Figure 3.5 shows the combined effects of path loss, shadowing and multi-path on the channel model.

Figure 3.5: Path loss, shadowing and multi-path with distance. Source: (7)



All of the channel models included in the 3GPP study are implemented in the NYU mmWave module under the MmWave3gppChannel class. The class allows you to specify the scenario and also the LOS condition when designing your own simulations.

The module also implements the probabilistic LOS equations that are defined with the channel models. For each scenario, there is a LOS probability model which is a function of the 2D distance between the eNB and the UE. Figure 3.6 shows the model for probability of LOS in the RMa scenario.

The MmWave3gppChannel class allows you to use these probability models which will then select the correct LOS/NLOS path loss model from the MmWave3gppPropagationLossModel class depending on specified 2D distance in your simulation scenario. The probability can also be re-evaluated (thus also the LOS condition) at a defined period to account for the mobility of the user in your simulation.

Figure 3.6: RMa LOS Probability. Source: (6)

Scenario	LOS probability (distance is in meters)
RMa	$P_{LOS} = \begin{cases} 1 & , d_{2D} \leq 10\text{m} \\ \exp\left(-\frac{d_{2D}-10}{1000}\right) & , 10\text{m} < d_{2D} \end{cases}$

NYU also implemented a propagation loss model class that can be used with the presence of buildings; MmWave3gppBuildingsPropagationLossModel. In this model, the LOS condition (LOS or NLOS) is determined according to the relative position of the UE, the eNB and the buildings defined during the simulation design stage. If the trajectory of a straight line from the eNB and the UE collides with a building, the NLOS model is used. This LOS/NLOS condition can also be updated at a defined update period which is important for simulations with UE mobility.

It is important to reiterate that with the 3gppBuildingsPropagationModel, the buildings themselves (such as the material of the building) do not factor into the calculation of propagation loss. The same channel models, an example shown in Figure 3.4, are used with the buildings propagation model. The buildings in the simulation design are only used to enforce NLOS conditions and in turn to force the simulation to use the NLOS channel model.

Ray-Tracing or Measurement Trace Model

The Ray-Tracing or Measurement Trace Model, uses software-generated or measurement traces to model the channel in ns–3 for path loss and fading (4). These traces are defined before the simulation is executed and contain the number of paths, the propagation loss, delay, angle of arrival and angle of departure for each path. The traces can be created using ray-tracing software such a WinProp, a Propagation Modelling tool, that allows you to build 3D models of areas and can be used to generate the channel model for a specific area.

This channel model would be useful for modelling very specific and detailed 3D scenarios such as modelling an actual area in a city. It would allow you to simulate how 5G would perform in this area which would in turn help when designing efficient 5G infrastructure deployment scenarios in the area.

NYU Statistical Model

The NYU Statistical Model was designed by the NYU researchers and has been used in their previous work; "5G mmWave Module for ns-3 Network Simulator" (40). The model contains two channel model classes which differ in how they handle the LOS/NLOS condition. The first, MmWavePropagationLossModel, is based on a statistical characterization of the LOS state, while the second, BuildingsObstaclePropagationLossModel, uses the buildings module in ns3 in order to determine if there is LOS or not (40). The model uses MATLAB traces which makes the computation less demanding, but is available only for the 28 and 73 GHz frequencies (40).

<u>Chosen Model:</u> 3GPP Statistical Channel Model

As 3GPP set the standards in cellular networking, I decided to choose the 3GPP Statistical Channel Model which utilises the work outlined in their 5G channel modelling study (6). The scenarios as outlined in the study are also fully built into the module so I can easily switch between them and evaluate performance in each scenario. The authors of the NYU paper on simulating end-to-end 5G networks also state that the 3GPP channel model is the most flexible and detailed channel model of the three available (4).

3.4.3 The Physical Layer

The Physical Layer is responsible for moving bits from one device to another. At the Physical Layer, the NYU mmWave module implements a Time Division Duplex (TDD) frame and subframe structure. TDD describes the separation of uplink and downlink transmission on the time domain as the Base Station is unable to both send and receive data at the same time.

It is widely contended that 5G mmWave systems will target TDD as it allows the systems to fully utilise the available bandwidth (5). Each user is allocated uplink and downlink time by the Base Station (BS) using control signals. For instance, when a UE wants to send data upstream, along with the ACK (Acknowledgement) message it sends on receiving data, it sends a scheduling request (SR) to the BS. The BS then allocates a time using the scheduler to receive the data from the UE. When the time arrives, a Grant message is sent to the UE and on receiving the Grant message, the UE begins uplink data transmission. The uplink and downlink transmissions in this case are protected by a guard period. The guard period is where no transmission is sent in either direction. This is to protect transmissions from colliding which would result in interference.

This kind of TDD implementation is only made possible because mmWave signals are highly directional. With previous LTE implementations, uplink and downlink switching had to be coordinated between neighbouring base stations as the signals LTE antenna arrays produce are omni-directional. This means that uplink and downlink transmissions cannot be assigned differently in neighboring cells since the downlink transmissions would overwhelm the uplink ones and the uplink transmissions would not reach their intended receiver (41). Because mmWave signals can be directionally isolated, it allows for dynamic TDD scheduling where uplink and downlink transmissions can be assigned dynamically (42). This system allows UEs to prioritise their traffic direction and means they are not left waiting for other neighbouring Base Stations to also send traffic in the direction they want.

The mmWave module implements a frame structure as shown in Figure 3.7. It allocates 1Ghz of bandwidth per user which is divided into 72 subbands of width 13.89 MHz. Previous mobile generations would allocate this frequency bandwidth by sharing the subbands between users, but in this case the entire bandwidth (all 72 subbands) is allocated to one user using the TDMA MAC scheme which is further discussed in Section 3.4.4.

Figure 3.7: Frame Structure. Source: (4)

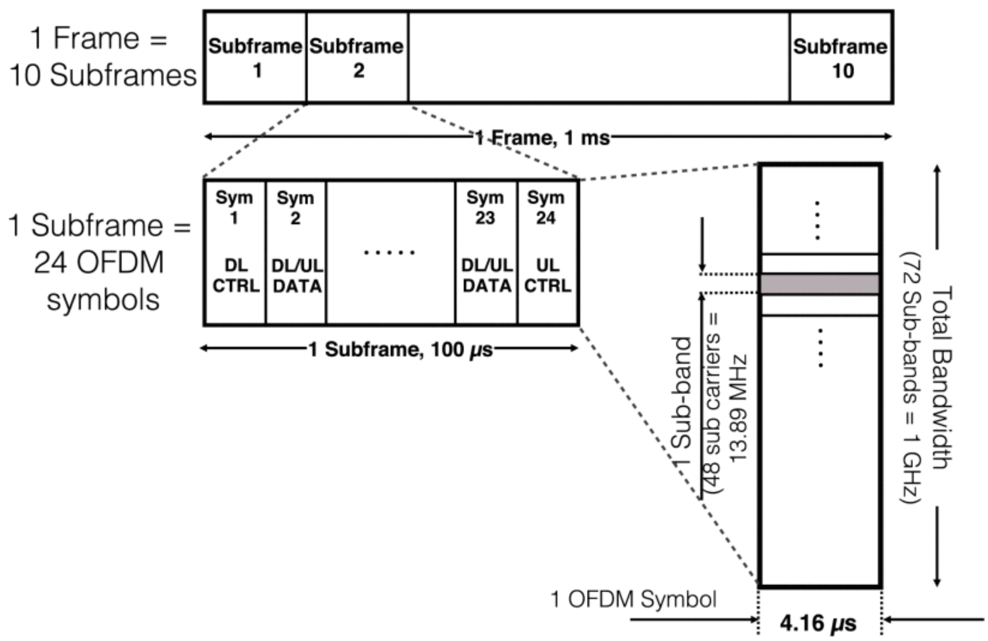


Figure 3.7 also illustrates the frame and subframe structure. Each subframe contains the uplink or downlink data and also the control signals. The frame structure can be adjusted in the MmwavePhyMacCommon class. I chose to use the frame structure provided as it was designed by NYU specifically for mmWave systems and detailed in their 2017 paper (41).

3.4.4 The MAC Layer

The Medium Access Control (MAC) layer is responsible for moving data packets from one network interface to another over a shared channel. As mentioned in Section 3.4.1, the mmWave module implements a Time Division Multiple Access (TDMA) MAC scheme where all users recieve the same bandwidth which is allocated on the time domain.

TDMA is largely accepted as the defacto scheme for mmWave access (4). This is because mmWave is dependent on analog beamforming. Analog beamforming is where the transmitter and receiver align their antenna arrays to maximize the gain in a specific direction. Previously in most conventional systems, these antenna arrays were aligned to increase angular spread and be omni-directional (4).

mmWave uses highly directional signals to maximise gain and so it would not be possible to allocate bandwidth from one signal to multiple users at the same time as was done in LTE which uses the Frequency-division Multiple Access (FDMA) scheme in the downlink. FDMA allocates bandwidth on the frequency domain rather than the time domain.

The NYU paper on end-to-end mmWave networks (4), cites that many early designs and prototypes of mmWave systems have been TDMA-based such as (42) and (43). Given that each user is allocated 1GHz in bandwidth at the Physical Layer, TDMA means the users will receive 1GHz in bandwidth in the downstream and upstream direction, thereby providing far more upstream bandwidth than is currently available in LTE networks. The TDMA scheme can be implemented with a number of schedulers, the default scheduler is a Round Robin scheduler. The scheduler is responsible for allocating data packets and retransmissions on the time domain fairly to all the users on the network.

The MAC layer is implemented in the MmWaveEnbMac and MmWaveUeMac classes. The main role of these classes is to coordinate procedures such as scheduling and retransmission.

The mmWave module MAC layer also implements the error-control technique Hybrid Automatic Repeat Request (HARQ) which was first introduced in "A class of adaptive hybrid ARQ schemes for wireless links" (44) and is extensively used in LTE networks (45). HARQ allows for fast retransmissions of lost packets with incremental redundancy which increases the probability of successful decoding and the efficiency of the transmissions (4). HARQ is particularly important in mmWave networks as its function is to mitigate against packet loss due to rapid variations in the channel quality which are commonplace in mmWave networks.

HARQ was available in LTE networks but it was limited to 8 HARQ processes per user. In the mmWave MAC scheme, the number of HARQ processes per user in the upstream and downstream is not fixed at 8 and can be allocated using the NumHarqProcesses attribute in the MmWavePhyMacCommon class. For my experiments, the value was left at its default which was 20 HARQ processes per user.

3.5 Simulating Video Traffic in ns-3: Evalvid

Following research into methods of simulating video traffic in ns-3, I found the ns-3 module Evalvid which was developed by Gercom, a Networks Research Group in Brazil. Evalvid was originally developed and released for ns-2 by the Technical University of Berlin, Telecommunication Networks Group (TKN) (46). After TKN ceased development of the module, Gercom updated the code to be compatible with the new ns-3. The module was distributed with examples that showed how to simulate video traffic in ns-3 both with a simple client-server setup and also with an LTE network.

The module has two classes, a server class and a client class. On startup the client sends a message to the server requesting the video transmission. During the server setup, the server reads in a video trace file so that it can accurately simulate the video transmission. The transmission of video over the network uses UDP sockets.

The video trace file is generated using Evalvid's mp4trace tool which streams an mp4 file to a specified localhost on your machine (so there would be no loss of quality) and generates a trace file of this transmission. The trace file contains information such as frame type, frame size, number of packets and packet interval for each frame of video. This information then allows the Evalvid server to simulate the same packet transfer profile in your ns-3 simulation by reading in that packet profile and creating the packets to match in real-time.

At the client, it receives the packets and creates its own trace file of packets received. Once the simulation is finished, the etmp4 (Evaluate Traces of MP4-file) tool can be used to recreate the transmitted mp4 file by passing the tool the original mp4 video, the senders trace file and the receivers trace file. You now have an mp4 file which accurately represents the quality after being transmitted through the end-to-end network.

The Evalvid module was initially designed and released for a version of ns-3 which is now over six years old and so unfortunately it did not work straight out of the box when combined with the latest versions of ns-3 that support the newer 5G modules such as the mmWave NYU module.

For example, initially I found that the packet that is sent from the client requesting video transmission was not arriving at the server. After a lot of testing and debugging I discovered that the method of instantiating a packet in ns-3 had changed in recent releases and so the packet was failing to be created. The process of debugging issues like these was time-consuming but ultimately successful and allowed me the opportunity to greater understand the code and technologies behind both Evalvid and ns-3.

Now that I understood how Evalvid works, I could easily merge it with my 5G implementation. The application module in ns-3 allowed me to install the server and client classes on specific network nodes and in turn these classes act as applications.

In this case, as we wanted to simulate video transfer in the upstream direction, I installed the server on the UE device and the client on the remote host. To validate that the applications were working, I used logs printed by the client and the server both sending and receiving packets, and validated that the IP address of the device sending the packets matched the IP address I had assigned to the UE and similarly the IP address receiving the packets matched the IP address I had assigned to the remote host.

Following this development, I now had a working 5G end-to-end network simulation which could also simulate video transfer in the upstream direction.

3.6 Simulation Validation

Once I had the simulation designed, I needed to validate it by comparing output from my simulation with output obtained with a known validated simulation.

Figure 3.8 shows path loss in dB with 3D distance for three of the scenarios outlined in the 3GPP study. These graphs were included in the NYU paper on designing mmWave end-to-end networks and were obtained by extracting the path loss from a simulation they designed which used the 3GPP channel models (4).

I attempted to recreate these graphs with my own simulation as validation and the results are shown in Figure 3.9. While my graph is more limited in resolution, simply due to processing time, it follows the same trend and matches up with the values of NYU's graph at the same points for both LOS and NLOS conditions.

Following successful validation, the simulation was ready to run experiments.

Figure 3.8: NYU 3GPP simulation output. Source: (4)

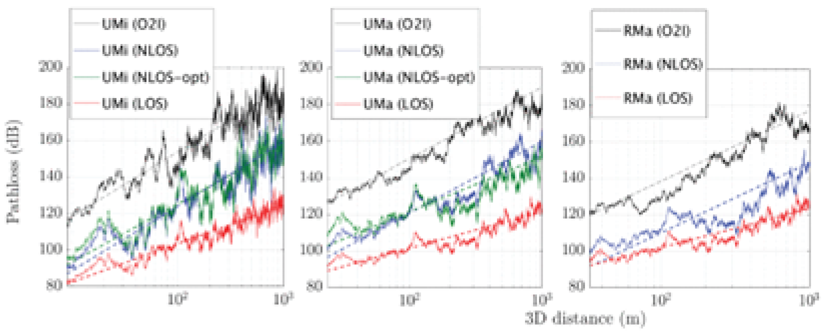
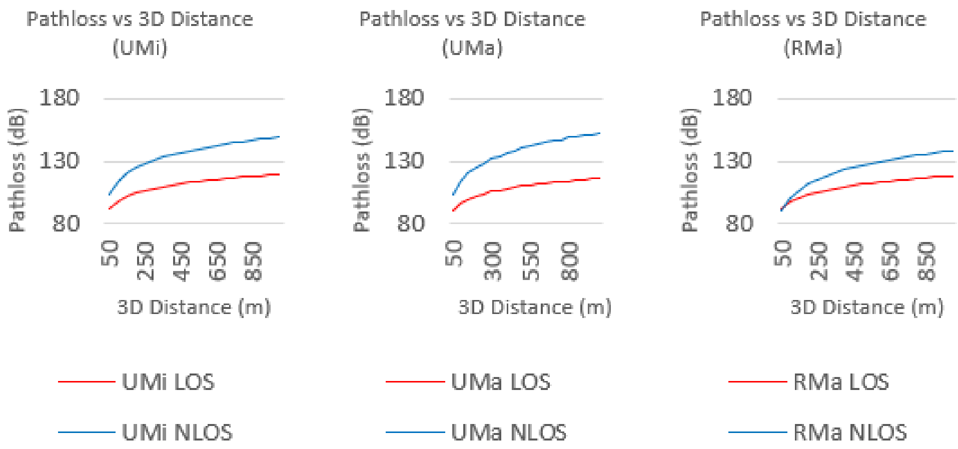


Figure 3.9: My Validation Results



3.7 Determining Quality of Experience

As outlined in Section 2.4, there is 5G literature that uses machine learning techniques to predict QoE in 5G networks (31, 32). But the purpose of this body of research is to use QoE as a metric for gauging performance of upstream video traffic in 5G networks, not to evaluate if machine learning can or should be used to predict upstream video QoE.

Therefore following the research outlined in Section 2.3, I decided to use the Video Quality Metric (VQM) assessment to evaluate the Quality of Experience at the remote host. I chose this metric given the accuracy of the results it has shown compared to other QoE metrics (3) and also given its popularity in QoE research (21).

The software was available on a Git repository maintained by the NTIA and it is also available free of charge for any commercial or non-commercial use. It works on Windows machines and requires the MATLAB R2013b (8.2) Runtime to be installed prior to use. The Git provides multiple software packages such as the Batch Video Quality Metric software which allows you to compare multiple test videos to the reference video in one operation and also the Command Line Video Quality Metric software which allows you to run the operation on the command line.

I chose to use the Batch Video Quality Metric software as I could then evaluate the multiple videos obtained through experiments against the reference video at the same time. I also found that the other versions of the software failed to compile, citing that an older version of the MATLAB Runtime was required, a version which is no longer publicly available on the MATLAB website.

The software requires the videos to be in raw format (YUV) with a chroma subsampling of 4:2:2. I obtained these videos from the Consumer Digital Video Library.

The Consumer Digital Video Library (CDVL) is maintained by the Institute for Telecommunication Sciences, the research and engineering laboratory of the National Telecommunications and Information Administration, United States Department of Commerce.

The introduction on their website describes the library as a "digital video library intended for researchers and developers in the fields of video processing and visual quality (both objective and subjective assessment)" (47). The library contains raw video files (i.e. uncompressed) that are licensed to be used in academic research. The library contains videos in many different formats including resolution formats of CIF (352x288) all the way up to True 4K resolution (4096x2160) which is the original resolution that Netflix films with their production cameras.

The VQM software comes with multiple models which can be used to obtain a VQM score. The latest model is the Variable Frame Delay model. This model was used in Trinity research last year looking into QoE in LTE networks (21) but I found that when using this model the software failed during execution. Following many hours of debugging, I was unable to resolve the MATLAB error I was receiving and instead I tested using the NTIA General Model which been noted in academia as having high accuracy. The test was successful and I was able to obtain a VQM score using a test and reference video.

Even though the General Model is not as accurate as the Variable Frame Delay model, they are still very similar and I decided that as long as the same model is used throughout the experiments, then we would be able to accurately compare and contrast results between experimental scenarios. The QoE research in this work is used to give a sense of the user's experience in different experiment scenarios contained within this research and not in comparison to metrics obtained in other bodies of research.

3.8 Full Experiment Process

Now that I had a simulation designed and I could determine QoE, I could proceed to run experiments and gather results. The full process has been detailed below:

(1) **Obtain sample video from Consumer Digital Video Library**

It is predicted that the strong capabilities of 5G networks such as higher bandwidths, lower end to end delays and improved reliability will increase demand for mobile video consumption. This increase in demand will also coincide with the availability of portable devices with 4K (UHD) or even 8K screen resolutions (33).

Given this, I chose two standards of video for my experiments, one at 1920x1080 (HD) resolution with a frame rate of 30 frames per second and the other at 4096x2160 (True 4K) with a frame rate of 60 frames per second.

(2) **Convert raw video to mp4 using ffmpeg**

Videos in raw format are extremely large, for example, five seconds of uncompressed Netflix True 4K video content is around 7GB in size. It's simply not feasible to stream this much data in such a short period of time. To get around this problem videos are compressed, removing enough data to make real-time video streaming possible while still retaining enough quality for the user to enjoy the experience.

An example of a video compression technology is H.264 which was jointly published by the International Telecommunications Union (ITU) and the International Standards Organisation (ISO) (48). I chose to use this compression technology given its popularity in the video streaming industry. For example, using H.264 is a broadcasting requirement of the popular live-streaming platform Twitch.tv (49). I used ffmpeg to perform the compression. ffmpeg is a popular command line tool which can be used to record, convert and stream audio and video.

(3) **Generate the video trace file**

As described in Section 3.5, the video trace file is generated using Evalvid's mp4trace tool.

(4) **Design the simulation scenario:**

Now that I had the video trace file ready, it was time to design the network scenario. The simulation allows the user to adjust the following parameters:

- Channel Model: RMa, UMa or UMi-StreetCanyon
- Line of Sight: LOS, NLOS or probabilistic LOS
- Mobility of the UE: Enabled or Disabled
- Velocity of the UE: If mobility is enabled, the velocity in m/s of the UE
- Buildings: Enabled or disabled, you can also adjust the shape/size of buildings
- Distance: Distance of the UE from the eNB at time = 0
- Shadowing: Enable or disable the shadowing component of the channel model
- Carrier Frequency: The spectrum band of the carrier frequency
- Hybrid Automatic Repeat Request: Enabled or disabled

(5) **Run the simulation using a Python script**

To collect multiple results at once, I wrote a Python script that would run the simulation multiple times with a UE-eNB distance increment on each run.

The Python script opens a sub-process and executes the ns-3 simulation on the command line. The simulation accepts a command line distance argument that overrides the distance parameter in the simulation C++ file. This allowed me to run the same simulation but adjust the distance of the UE from the eNB each time. The name of the receiver trace file is then formatted each time to include the distance so as to uniquely identify the trace file on each run.

When the simulations have been run, the Python script then initiates more command line subprocesses that process the receiver trace files and generates the mp4 files using the etmp4 Evalvid command line tool.

Now that we have run the simulation and have recreated the mp4 files on the receiver side, we can evaluate the QoE.

(6) **Evaluate the QoE using VQM**

It is now necessary to obtain QoE scores for the transmitted videos. To facilitate this, the mp4 videos are converted back into raw format (YUV) using the ffmpeg tool, this is done using Python script to save time. This is necessary as the VQM software only performs its evaluations using YUV files.

The videos are then loaded into the Batch VQM software along with the original un-transmitted raw video (reference video). The software allows the user to identify which is the reference video and which are the videos the user wants to compare with it. It also allows the user to specify the height and width of the frames and the frame rate.

The NTIA General Model is then chosen as the evaluation model and the process runs. For large files like True 4K YUV files it can take a few hours to obtain results for a few 5 second videos.

Following the evaluation, a report is presented to the user which can be exported to CSV. This report contains the VQM score assigned to each video by the General Model.

This experiment process is now complete.

4 Results and Evaluation

4.1 Results

This section publishes the results of the simulation executed under a number of scenarios. A scenario table outlines the parameters for each experiment and the graphs displayed for each experiment show both the packet loss % with 2D distance and the VQM score with 2D distance. The 2D distance in the graphs represents the starting distance of the UE from the eNB in each experiment. For each experiment, multiple simulations are run with the starting distance adjusted each time. This adjustment was made at a 50m resolution.

In these experiments, low packet loss % and a low VQM score indicates good performance while high packet loss % and a high VQM score (>1) indicates poor performance. In the VQM Score vs 2D Distance graph, if the VQM score is not displayed, this indicates that the quality of the video was so poor that the VQM software was unable to obtain a valid score.

Experiment 1

The purpose of the first experiment is to establish a base line of performance with HD video using different channel scenarios. All parameters are left at their default values and the same experiment is run with three different channel scenarios.

Table 4.1: Experiment 1 Parameters

Experiment 1 Parameters	
Video	1920x1080 30 FPS 20 Seconds
Channel Scenario	RMa (7GHz), UMa (28GHz), UMi-StreetCanyon (28GHz)
Mobility	No Mobility, No Velocity
Buildings	No Buildings
Shadowing	True
HARQ	Enabled
LOS	Probabilistic

Figure 4.1: Experiment 1, % Packet Loss with Distance

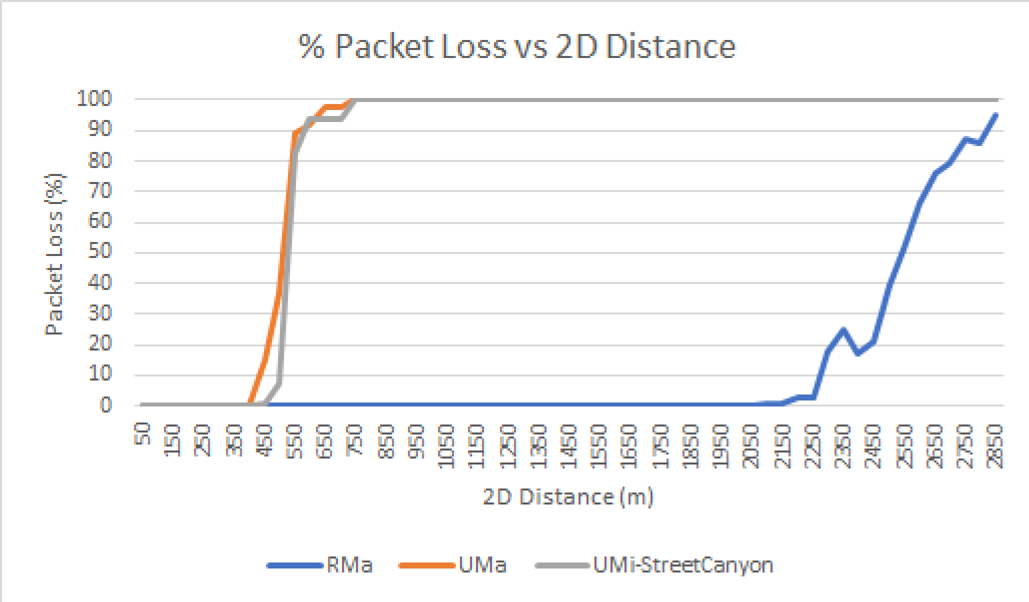
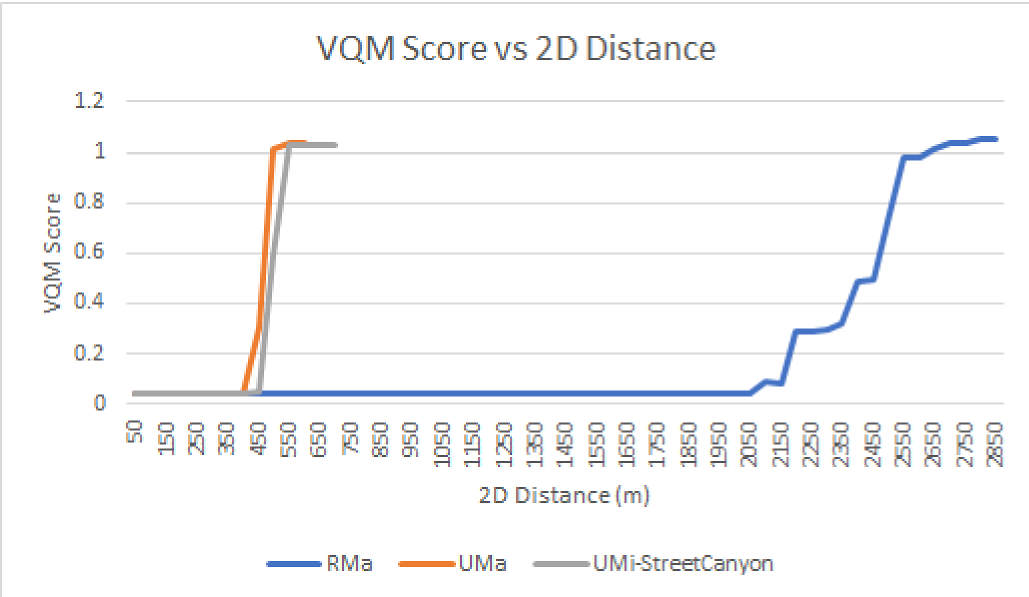


Figure 4.2: Experiment 1, VQM Score with Distance



Experiment 2

The purpose of Experiment 2 is to evaluate the performance of True 4K video transfer and to compare it with the results from Experiment 1. All other parameters remain the same.

Table 4.2: Experiment 2 Parameters

Experiment 2 Parameters	
Video	4096x2160 60 FPS 5 Seconds
Channel Scenario	RMa (7GHz), UMa (28GHz), UMi-StreetCanyon (28GHz)
Mobility	No Mobility, No Velocity
Buildings	No Buildings
Shadowing	True
HARQ	Enabled
LOS	Probabilistic

Figure 4.3: Experiment 2, % Packet Loss with Distance

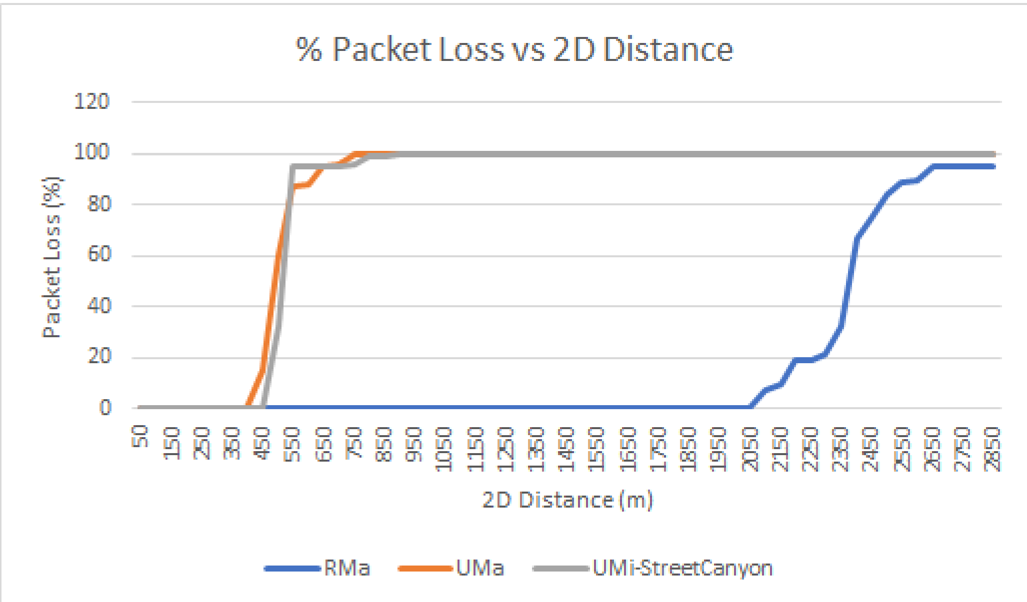
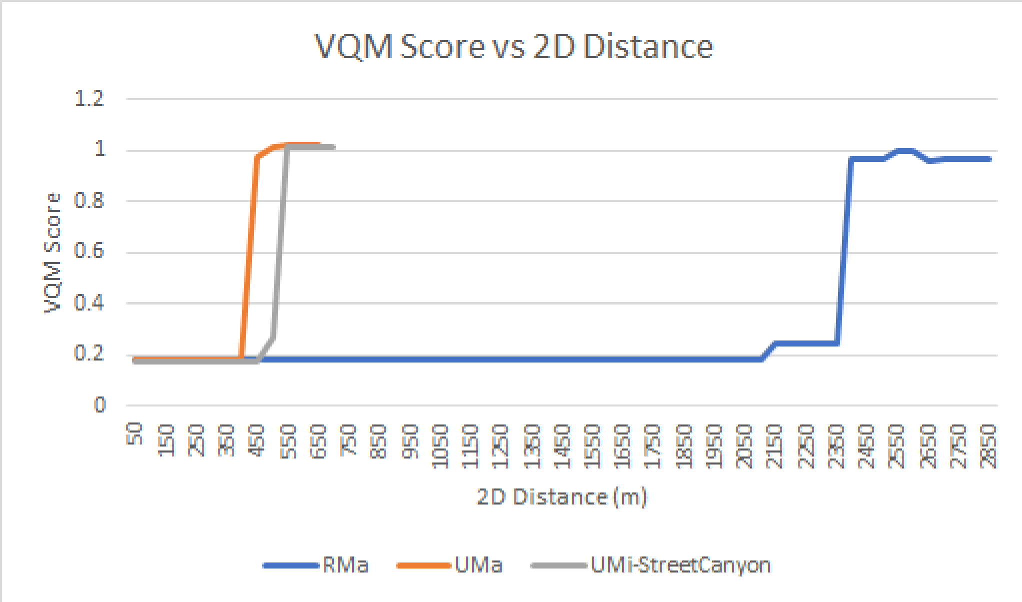


Figure 4.4: Experiment 2, VQM Score with Distance



Experiment 3

The purpose of Experiment 3 is to explore how carrier frequency can effect performance in NLOS conditions in Urban Scenarios. As mentioned in Section 3.4.2, penetration through buildings is not modelled in the channel models but the buildings can be used to block LOS between the eNB and UE and thus cause NLOS conditions. We can use this feature to give us a sense of performance in NLOS conditions and how the models represent the capability of reflection and diffraction as a method to maintain communication around obstacles.

In this experiment a building is constructed at 50 meters from the base station, the simulation is run with the user behind the building forcing NLOS conditions. The carrier frequencies chosen were 28GHz, 60GHz and 73 GHz, specifically targeting the oxygen absorption zone (57-64 GHz) to investigate its effects.

Table 4.3: Experiment 3 Parameters

Experiment 3 Parameters	
Video	1920x1080 30 FPS 20 Seconds
Channel Scenario	UMa (28GHz), UMa (60GHz), UMa (73GHz)
Mobility	No Mobility, No Velocity
Buildings	Buildings at 50 meters
Shadowing	True
HARQ	Enabled
LOS	NLOS due to buildings

Figure 4.5: Experiment 3, % Packet Loss with Distance

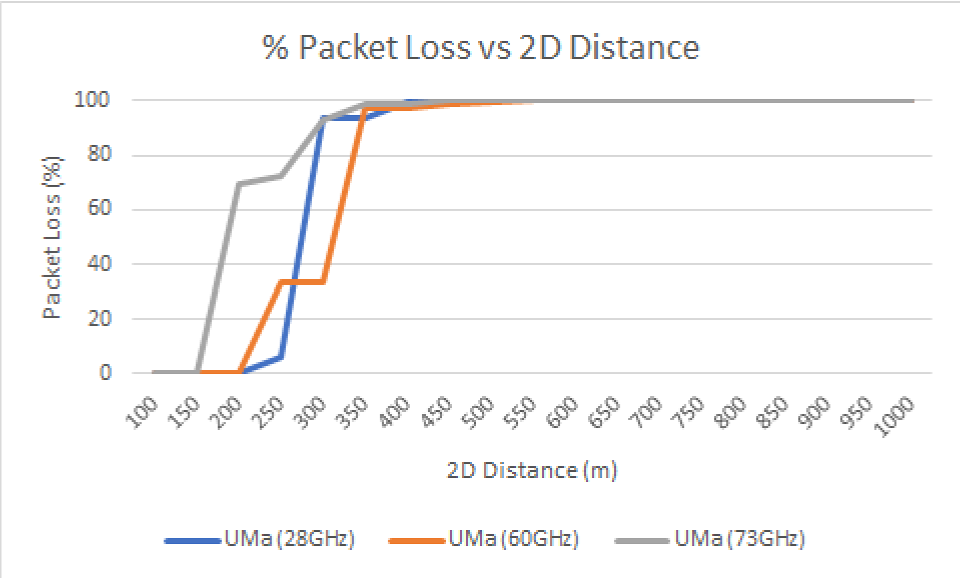
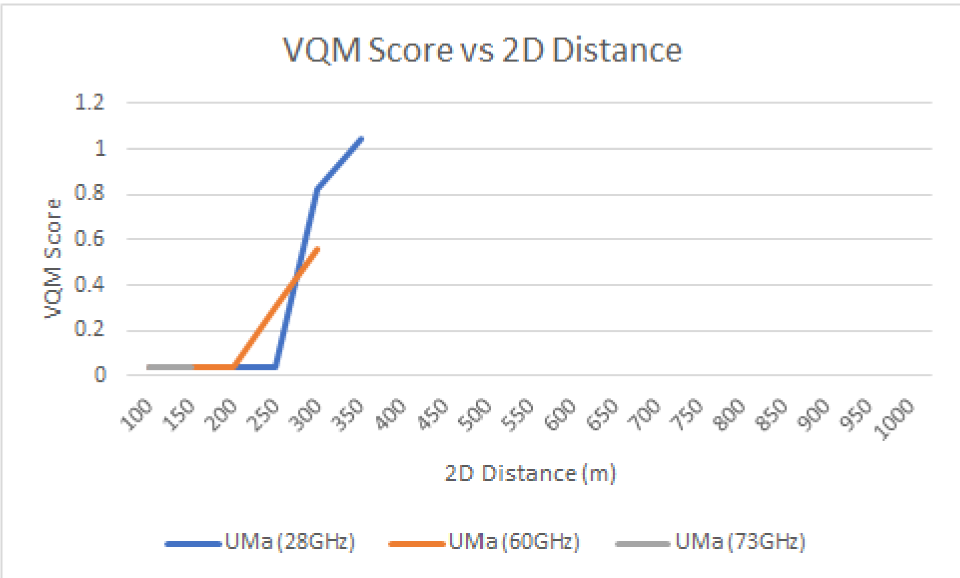


Figure 4.6: Experiment 3, VQM Score with Distance



Experiment 4

The purpose of Experiment 4 is to evaluate the impact of the MAC layer scheme Hybrid-ARQ on performance of packet loss and QoE at mmWave frequencies. The simulation is set up with the same parameters as Experiment 1; no velocity, no buildings and probabilistic LOS. The simulation is run using the UMa channel scenario at 28GHz and the graphs show a comparison between HARQ Enabled and HARQ Disabled.

Table 4.4: Experiment 4 Parameters

Experiment 4 Parameters	
Video	1920x1080 30 FPS 20 Seconds
Channel Model	UMa (28GHz)
Mobility	No Mobility, No Velocity
Buildings	No Buildings
Shadowing	True
HARQ	Enabled and Disabled
LOS	Probabilistic

Figure 4.7: Experiment 4, % Packet Loss with Distance

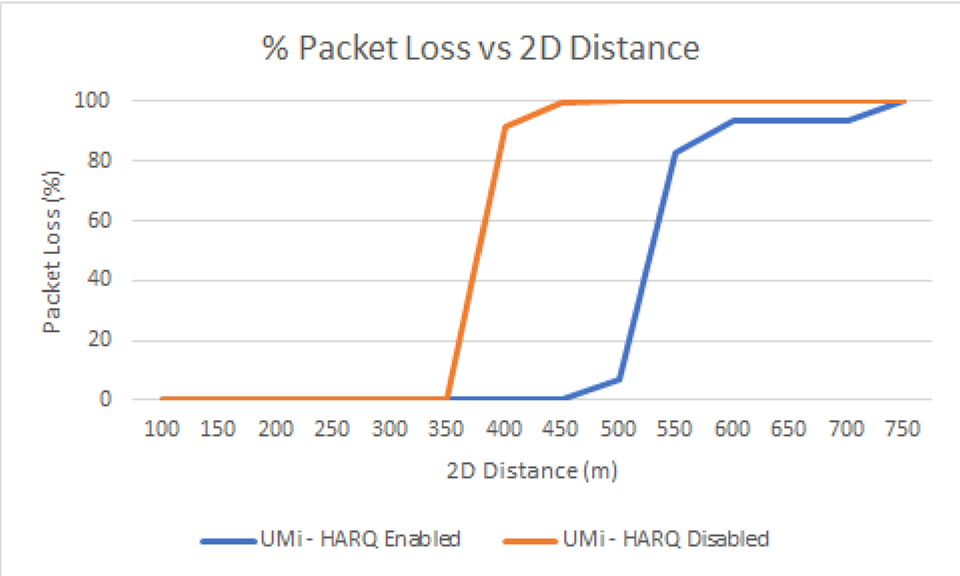
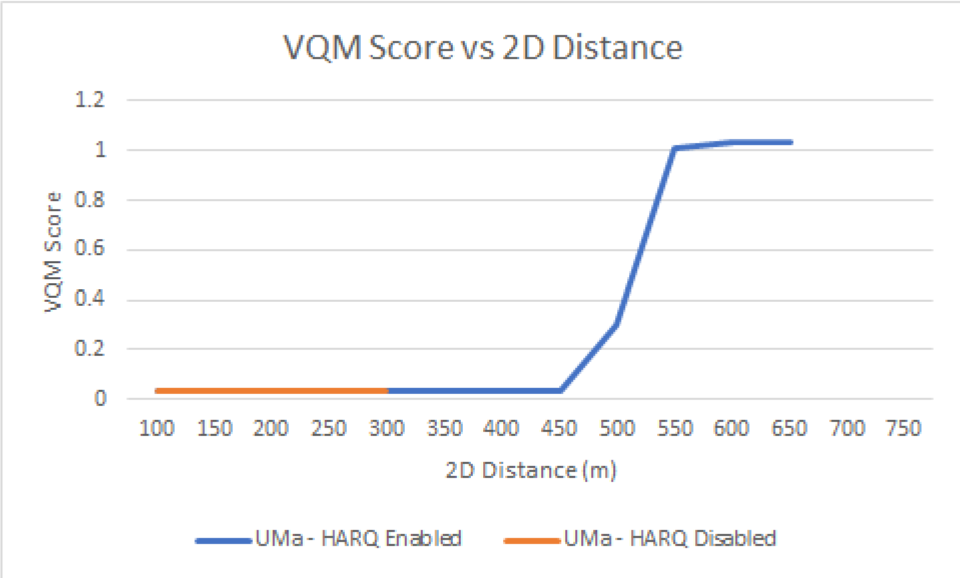


Figure 4.8: Experiment 4, VQM Score with Distance



Experiment 5

The purpose of Experiment 5 is to evaluate the impact of mobility on performance of packet loss and QoE at mmWave frequencies. The simulation is set up with the same parameters as Experiment 1 except the UE now has a constant velocity on the x-axis of 1.5m/s which is the average human walking speed. The user is moving away from the eNB on a straight line and the starting position is adjusted on each run. The 2D distance axis on the graphs below represents the starting distance between the UE and the eNB. The experiment is performed with the UMa and UMi-StreetCanyon channel scenarios at 28GHz.

Table 4.5: Experiment 5 Parameters

Experiment 5 Parameters	
Video	1920x1080 30 FPS 20 Seconds
Channel Model	UMa (28GHz), UMi-StreetCanyon (28GHz)
Mobility	Constant Velocity = 1.5m/s
Buildings	No Buildings
Shadowing	True
HARQ	Enabled
LOS	Probabilistic

Figure 4.9: Experiment 5, % Packet Loss with Distance

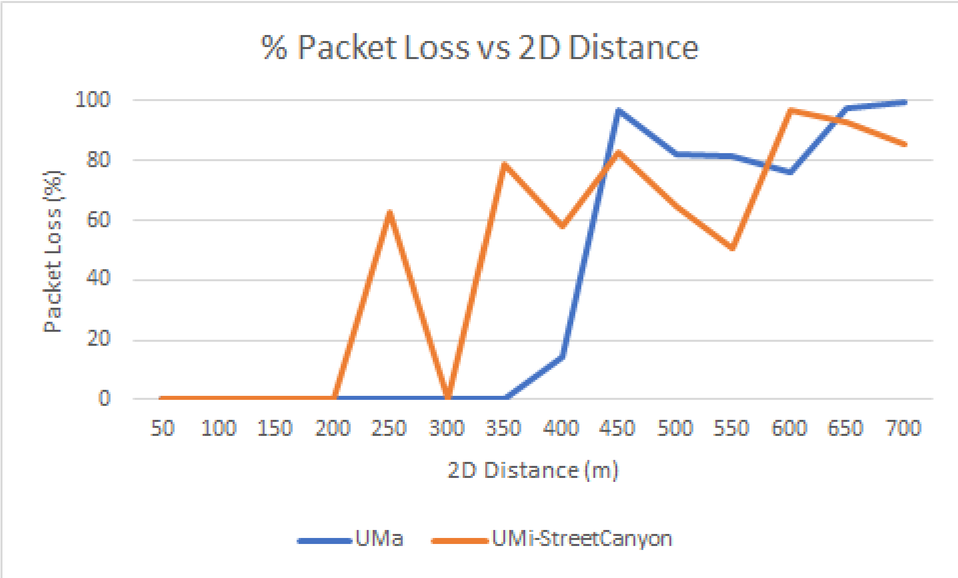
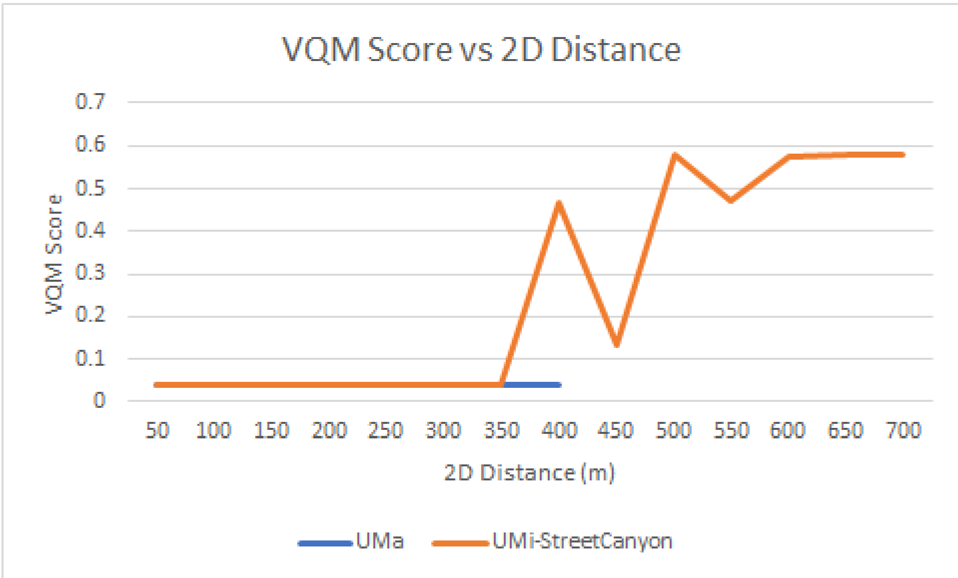


Figure 4.10: Experiment 5, VQM Score with Distance



4.2 Evaluation

Experiment 1

Experiment 1 shows us the difference in performance with distance between Urban and Rural scenarios. In Figure 4.1, we see a sharp drop off in performance with the Urban scenarios at around 400-550 meters compared with a more gradual drop off in performance starting at around 2200 meters in the Rural scenario.

The sharp drop off in performance in the Urban scenarios is almost certainly down to path loss attenuation caused by NLOS conditions. Even though the 7GHz Rural scenario and the 28GHz Urban scenarios have similar propagation distance in free space, given that the experiment uses the probabilistic LOS functions, the Urban scenarios go into NLOS conditions a lot earlier and this is shown by their sharp drop off in performance which is to be expected at the high 28GHz carrier frequency.

The Rural scenario also likely goes into NLOS conditions around 2000 meters but the drop in performance is not as severe due to the lower frequency.

If we compare Figure 4.1 with Figure 4.2 we can also see a high correlation between packet loss and the VQM metric. This is to be expected given the high correlation between Quality of Service parameters such as packet loss and Quality of Experience metrics such as VQM.

Experiment 2

Experiment 2, which has the same simulation parameters as Experiment 1 but transmits True 4K video, is very similar in performance profile to Experiment 1. In the Urban scenarios, the packet loss profile shown in Figure 4.3 is almost exactly the same. This really goes to show the impact that obstacles and blockages can have. The bandwidth available is more than enough to carry even 4K video but once the signal goes into NLOS conditions the attenuation and in turn the packet loss rise sharply.

The Rural packet loss profile is very similar to results shown in Experiment 1. We can see that the performance drop off starts slightly earlier, around 2100 meters, this is likely due to the higher bit rate required to transmit 4K video and so the there is a greater chance of packet loss at an earlier stage. More importantly it is evident that there is sharper drop off in QoE compared with Scenario 1 at the point packet loss begins. In Experiment 1, the VQM score gradually increases as packet loss increases, but in Experiment 2 even though the packet loss increases gradually, the QoE deters rapidly. This shows us that with 4K video, QoE is more susceptible to poor quality connections.

This experiment shows us that 5G has the capability to upstream extremely high quality video content with excellent QoE if LOS conditions can be maintained.

Experiment 3

Experiment 3 illustrates the severe impact on performance due to NLOS conditions, especially at high frequencies. The highest frequency 73GHz starts dropping packets at the shortest distance, around 150 meters. This shows that even in NLOS conditions, high performance HD video transmission is still possible up to 150 meters in Urban scenarios at 73GHz.

As expected, the 28GHz band performs the best of the three nevertheless the gap in performance between the three bands really isn't that large. There is only 50 meters between when the 73Ghz band fails to produce a VQM score and the initial rapid increase of the 28GHz VQM score. The lower band will only guarantee you high quality video for an extra 50 meters. This shows the truly severe effect NLOS conditions have on the quality of communications at mmWave frequencies.

One thing to note is there is no severe reduction in quality at 60GHz as would be expected due to oxygen absorption. Even though models of the oxygen absorption band exist in the 3GPP 6-100GHz channel modelling study (6), following research and examination of the mmWave module classes, it doesn't look like these models have been implemented into the module and therefore the performance of the 60GHz band is more than likely not accurately portrayed.

Experiment 4

Experiment 4 illustrates the impact of Hybrid-ARQ on performance. It can be clearly seen in both Figure 4.7 and Figure 4.8 that HARQ has a big positive impact on performance. Without HARQ, the network starts dropping packets at 300 meters and the packet loss is so great that at 350 meters a VQM score cannot be obtained on the video at the remote host due to the large amount of impairment. With HARQ enabled, the distance at which high Quality of Experience can be maintained in 450 meters, which represents a 50% increase. The eventual drop off in quality is also not as sharp.

This shows us that even at 300-450 meters, the communication channel between the eNB and UE starts experiencing errors. With HARQ detecting these errors and repeating packets, these errors can be greatly mitigated.

Experiment 5

The graphs obtained through Experiment 5 show a far more sporadic performance profile as the UE moves away from the eNB. In previous experiments with no mobility, as the UE was placed further and further away the performance got continuously and predictably worse.

In the case of Figure 4.9, we can see the packet loss performance at further distances is far less predictable. Packet loss % and the VQM score in Figure 4.10 move up and down on the y-axis even as the 2D distance increases. This is no doubt a result of shadowing. As the UE is moving, the shadowing factor increases and decreases on a Gaussian distribution simulating obstacles that the user passes along their path. The signal which is highly directional is trying to track the user's movements by using reflection and diffraction to bend the signal around these obstacles. These graphs essentially show that a moving target is much harder to hit.

In Experiment 4, Figure 4.7 showed us that HARQ was able to mitigate well against packet loss between 350-450m for the UMa channel scenario. But in this case, the combined effect of NLOS and a moving target is too much for the network to handle.

Despite the sporadic performance at long distance, performance close to the eNB for both the UMa and UMi-StreetCanyon scenario is still very good and high QoE is maintained up to around 350 meters.

5 Conclusion

In this work, I described an implementation of a 5G end-to-end network simulation that can simulate the transmission of video traffic upstream from a mobile device to a remote host. I also implemented a Quality of Experience framework which allows us to gain more insight into how 5G networks handle upstream video traffic in a range of scenarios. The network simulator used was ns-3, the end-to-end 5G network was implemented using the NYU mmWave ns-3 module and the video traffic was simulated using the Evalvid ns-3 module. The QoE assessment was performed using the VQM General Model developed by the NTIA.

Upstream video QoE in 5G networks has not been previously explored and the results in this work show huge potential for the future capabilities of live streaming services. In the right conditions, the next generation of mobile networking allows its users to share live experiences in extremely high quality thanks to the massive bandwidth provided by a combination of the large available bandwidth in the mmWave spectrum and implementations in the Physical and MAC layers such as TDD and TDMA.

The findings in this work also show the limitations 5G mmWave networks. While at short distances excellent quality can be maintained, as the user moves into Non-Line-of-Sight conditions the QoE drops rapidly. The QoE can be compounded further by mobility of the user as the highly directional mmWave signal tries to track the user using reflection and diffraction around obstacles. Industries that hope to utilise 5G upstreaming traffic such as the television industry will have to rely on both maintaining Line-of-Sight to their infrastructure and on implementing MAC layer techniques such as HARQ which can catch errors and maintain stable video quality even with rapid fluctuations in channel quality.

The poor propagation characteristics of mmWave through obstacles will create huge challenges both logistically and financially. But with the correct implementation which can deliver the requirements that 5G promises to offer, the next generation of mobile communication will allow its users to share their experiences in incredible detail and allow their audiences to experience the world as if they were there themselves.

The research presented in this paper offers the framework for a 5G end-to-end network that can simulate video traffic upstream, but it cannot be denied that the development of 5G elements in academic network simulators such as ns-3 is still in its early days. As we learn more about how the industry actually implements 5G infrastructure in the real world and development continues on more ns-3 modules which conform to the newest standards in 5G networking (such as 5G LENA), 5G end-to-end network simulations will become even more accurate and allow us to further explore what the future generation in mobile networking has to offer.

5.1 Future Work

The 3GGP channel models provided in the ETSI technical report on channel modelling in the 6-100GHz range also includes indoor scenarios such as an indoor office scenario and an indoor shopping-mall scenario (6). I decided to focus my research on outdoor scenarios but research in the area of indoor scenarios will be very important in determining QoE in areas where there would be a variety of blockages which would cause a large amount of reflection and diffraction.

This work focused on analysing the performance and limitations of the high frequency base stations (such as mmWave) that will be the forefront of 5G networks and it reveals the necessity, as mentioned in Section 2.1.2, for a high densification of 5G infrastructure which should help compensate for the poor propagation characteristics of high frequencies in Urban areas.

This creates a separate challenge as users will be often moving from one eNB to another and may also be moving at a very high speed in a car or a train. This handover of data exchange from one eNB to another will need to feel seamless for the user, and so research into how this handover may effect QoE would be both interesting and necessary.

Given that it will inevitably be years until enough 5G infrastructure exists to provide high coverage, there will be also the issue of handling switching between 4G eNBs and the expanding 5G infrastructure. Given the cost of implementing such a high densification of infrastructure required for 5G, it's likely that 4G infrastructure will remain long after 5G becomes mainstream and 4G will still be used to provide coverage in many low density areas. The switching between the generations of mobile infrastructure must again feel seamless to the user and work could be done to research how current implementations of the Physical and MAC layers handle this change.

An obvious point of contention with the results obtained through this research is that the scenarios tested assume the ideal condition that there is only one user actively connected to the eNB and it might be assumed that future work would involve increasing the number of devices in the simulation.

However, I noted in Section 3.4.1 that the Time Division Multiple Access (TDMA) MAC scheme implemented in the NYU module means that bandwidth is allocated to users only on the time domain and not the frequency domain. This means that adding a few more UEs would not have any effect on bandwidth allocation to the users. The main source of bandwidth limitation would be the scheduler that actually handles the bandwidth allocation on the time domain and the possibility that with an extremely large number of users, some users would fail to receive enough resources allocated to them on this time domain. However given the requirements of 5G, it would in all probability take simulating many thousand devices before any real impact on performance would be noticed.

Currently the complexity of the 5G models in ns-3 means that designing a simulation on this scale is simply not feasible even on a very high-end consumer PC. This will inevitably be a challenge for any future academic research in the area.

Finally, this work focuses on UDP video streaming which is more popular with livestreaming services that aim for low latency times between the video broadcaster and the eventual consumer, but a large proportion of mobile video traffic is TCP. TCP provides unique challenges due to the massive but intermittent bandwidth capacity available with mmWave cellular networks, as outlined in (50). These challenges will have to be explored as they relate to video traffic in both the upstream and downstream direction.

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