



Deposited via The University of Leeds.

White Rose Research Online URL for this paper:

<https://eprints.whiterose.ac.uk/id/eprint/241972/>

Version: Accepted Version

Proceedings Paper:

Chyad, A., Shah, S.D.A., Qazzaz, M.M.H. et al. (2025) Modelling 6Dof Vr Gaming Traffic for Next-Generation Networks. In: 2025 Joint European Conference on Networks and Communications & 6G Summit (EuCNC/6G Summit). European Conference on Networks and Communications (EuCNC), 03-06 Jun 2025, Poznan, Poland. Institute of Electrical and Electronics Engineers (IEEE), pp. 157-162. ISBN: 979-8-3503-9181-7. ISSN: 2475-6490. EISSN: 2575-4912.

<https://doi.org/10.1109/eucnc/6gsummit63408.2025.11037170>

Reuse

This article is distributed under the terms of the Creative Commons Attribution (CC BY) licence. This licence allows you to distribute, remix, tweak, and build upon the work, even commercially, as long as you credit the authors for the original work. More information and the full terms of the licence here:

<https://creativecommons.org/licenses/>

Takedown

If you consider content in White Rose Research Online to be in breach of UK law, please notify us by emailing eprints@whiterose.ac.uk including the URL of the record and the reason for the withdrawal request.

Modelling 6DoF VR Gaming Traffic for Next-Generation Networks

Ahmed Chyad* Syed Danial Ali Shah* Mohammed M. H. Qazzaz* Maryam Hafeez* Syed Ali Raza Zaidi*

*School of Electronic and Electrical Engineering, University of Leeds, Leeds, UK

*Corresponding author: Ahmed Chyad (elaamah@leeds.ac.uk)

Abstract—The increasing adoption of Extended Reality (XR) applications demands advanced traffic modelling to optimise next-generation wireless networks. Existing models often rely on fixed data rates (e.g., 50 Mbps) and frame rates (e.g., 60 Hz), which are insufficient for modern VR systems. This paper introduces an enhanced traffic modelling framework for highly interactive 6-degree-of-freedom (6DoF) VR gaming, incorporating video, audio, and control streams with support for higher frame rates (up to 120 Hz) and data rates (up to 251.9 Mbps). Built on empirical data from a high-fidelity VR setup, the model uses statistical analysis to fit data rate and inter-arrival times to probability distributions. The generalized logistic distribution is identified as the best fit for data rates, while the generalized extreme value distribution accurately represents inter-arrival times. Model accuracy is validated using Kullback-Leibler divergence. The findings offer critical insights for traffic generation, network planning, and resource allocation, supporting scalable and immersive XR experiences in future wireless networks.

Index Terms—Experimental VR traffic generation, VR traffic modelling, Edge computing.

I. INTRODUCTION

The Extended Reality (XR) sector is projected to grow significantly, reaching approximately 345.9 billion USD by 2030, with a compound annual growth rate of 33.09% from 2022 to 2030 [1]. As XR applications expand across industries such as entertainment, healthcare, education, and industrial training, the demand for robust network and processing systems becomes critical. XR applications require low latency and high throughput to ensure seamless user experiences, as delays can lead to desynchronisation in multi-user environments, motion sickness, and compromised real-time interactions in latency-sensitive applications like medical procedures or industrial control systems. Insufficient bandwidth further exacerbates issues, causing low-resolution streaming and network congestion.

To address these challenges, IEEE and 3GPP standards specify that motion to photon latency should not exceed 20 ms, with wireless transmitter to receiver delays below 5 ms [2], [3]. XR applications also demand data rates ranging from 2.25 to 27 Gbps, depending on resolution, frame rate, and compression techniques, while maintaining a packet error rate (PER) below 10^{-2} . These stringent requirements underscore the need for advanced traffic modelling and network optimisation tailored to XR services. However, existing models often rely on outdated assumptions regarding data rates, frame rates, and interactivity. This paper addresses this gap by proposing

an enhanced traffic modelling framework designed to meet the demands of modern, highly interactive VR applications, particularly those with 6DoF.

A. Related Works

Several studies have analysed VR traffic characteristics and proposed models for simulation. Zhao et al. examined cloud-based VR gaming traffic using a testbed that collected data from Beat Saber and Steam VR Home. Their analysis identified key application-layer characteristics, concluding that interarrival times follow a Burr distribution, while frame sizes fit a log-logistic model [4].

Lecci et al. developed a VR traffic model using traces from commercial VR streaming software, capturing the bursty nature of VR traffic but excluding audio and head movement data. Their ns-3 applications generated large packet bursts, enabling end-to-end metric analysis. Although simplified and neglecting second-order statistics, their model aids VR network optimisation [5]. Later, Lecci et al. expanded their study by collecting over four hours of VR traffic from applications like Minecraft VR and Google Earth VR, introducing a more comprehensive synthetic traffic model and publicly releasing their dataset [6].

Other studies provide relevant insights despite not focusing specifically on VR. In [7], a traffic characterisation of Counter-Strike was presented based on a 36-hour LAN party measurement, offering useful client-server traffic modelling insights applicable to VR gaming. Additionally, Alhilal et al. analysed network traffic in social VR platforms such as Mozilla Hubs, Spatial, and Meta Workrooms, identifying congestion issues related to avatar and model loading. While not strictly a traffic modelling study, their findings highlight key considerations for optimising social VR platform design [8].

B. Contributions

Accurately estimating XR traffic is essential for the successful operation of wireless networks supporting XR services. The key contributions of our study are as follows:

- **Development of a Comprehensive VR Traffic Model:** We designed a traffic model that considers video, audio, and control data streams exchanged between the VR Edge Server and the Head-Mounted Display (HMD). Our model focuses on the unique requirements of 6DoF interactive VR games.

- **Rigorous Statistical Analysis:** We conducted an extensive evaluation by fitting thirty-two statistical distributions to VR traffic data, a significant expansion compared to prior studies, which typically analyse no more than seventeen distributions.
- **Higher Frame Rate Analysis:** Our study uniquely analyses VR traffic traces collected at 120 fps, surpassing the 60 fps limit of most previous research [4]–[6], this higher frame rate reflects modern VR system requirements, offering a more accurate representation of real-world VR traffic.
- **Support for High Data Rates:** Unlike prior research focused on VR traffic with data rates around 50 Mbps, our model supports maximum data rates of 251.98 Mbps, addressing the demands of high-quality VR applications.
- **Creation of a New Dataset:** We generated a dataset by collecting traffic data from our offline VR setup, accurately reflecting the network demands of 6DoF VR games.

The rest of the paper is structured as follows: Section II shows the apparatus used as well as the settings and configuration of the testbed. The VR traffic, especially data rate and interarrival time, are analysed in Section III. The traffic models are proposed in Section IV, while the VR traffic generation and validation are in Section V. Ultimately, the conclusions and future works are drawn in Section VI.

II. TESTBED AND CONFIGURATION

Our experimental setup consists of a VR gaming environment where an end-user streams VR content from an edge server over a Wi-Fi connection, as illustrated in Figure 1. The specifications of the testbed equipment are detailed in Table I. The system supports high-performance VR applications, specifically *Propagation VR* and *Contagion VR: Outbreak*, with hardware exceeding the minimum requirements for these applications.

The network architecture follows a single-hop topology, where the Meta Quest 3 (MQ3) headset connects wirelessly to a Wi-Fi 6 router. The edge server is connected via a Cat 5E Ethernet cable, ensuring a stable wired connection with an average ping time of 1 ms. SteamVR software manages the pairing between the MQ3 headset, controllers, and the edge server, enabling real-time rendering and interaction. Network performance monitoring was conducted using Wireshark, installed on the edge server to capture traffic data over continuous sessions exceeding one hour.

To simulate realistic VR streaming conditions, no constraints were imposed on data rate or frame rate. The maximum supported frame rate is 120 Hz, and resolution settings were configured at the highest levels. SteamVR encoding settings were optimised to prioritise visual quality over performance, and hardware video decoding was enabled to offload high-resolution video processing from the CPU to the GPU. This hardware acceleration approach enhances system efficiency, resulting in smoother playback and faster rendering.

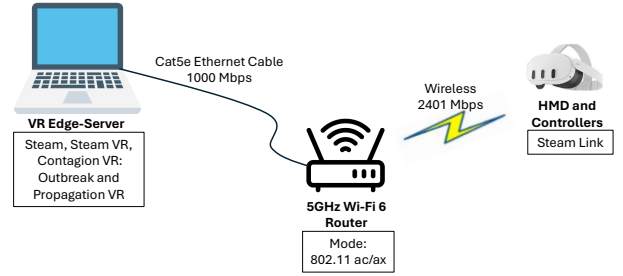


Fig. 1: Offline VR gaming diagram

TABLE I: Equipment Used in the Testbed Along with Their Specifications

Equipment	Specifications
Edge Server	Intel Core i9-14900HX laptop (24 cores, 32 threads, 2.2 GHz), 32 GB RAM, NVIDIA RTX 4080 (12 GB VRAM)
VR Headset	MQ3, Refresh rate 72 Hz, 90 Hz, 120 Hz, 8GB RAM, supports Wi-Fi 6E
Router	Wi-Fi 6 (IEEE 802.11ax), 5 GHz, max link speed: 2401 Mbps

The encoding mechanism employed is NVIDIA NVENC, which supports H.264 and HEVC codecs. By leveraging dedicated hardware encoders and decoders separate from CUDA cores, NVENC provides full hardware acceleration, preserving CPU and graphics resources for other operations [9].

For VR content transmission, the Quick UDP Internet Connections (QUIC) protocol was used. Which offers advantages over TCP, including faster connection establishment, improved congestion control, and multiplexing to mitigate head-of-line blocking. These features make it particularly well-suited for latency-sensitive VR streaming applications [10].

QUIC traffic was categorized into five packet types: Initial, Retry, Handshake, 0-RTT, and Protected Payload. Among these, only Protected Payload packets carry gameplay data, while the others handle connection management. This classification highlights QUIC's efficiency in prioritising essential data transmission, ensuring low-latency VR streaming.

Traffic measurements were expressed in megabits per second (Mbps), a standard metric in network engineering due to its alignment with hardware specifications such as ISP speeds, router capabilities, and Ethernet throughput. This representation accurately reflects VR bandwidth requirements, facilitating precise performance evaluation.

III. VR TRAFFIC COLLECTION AND PROFILING

The network performance between the edge server and the HMD was analysed during gameplay sessions. The average network delay, measured using the ping command, was found to be 5ms, which meets the latency requirement specified in [2]. This low delay is critical for maintaining a seamless VR experience, as higher latencies are known to contribute to motion sickness and reduced immersion. The packet loss during gameplay was minimal; the maximum packet loss for both VR samples is 0.037%. This is significantly lower than the maximum allowable packet error rate of 10^{-2} specified in

the IEEE Standard [2], ensuring a reliable data flow between the edge server and the HMD.

For the analysis of traffic attributes, we divide the network traffic into two primary categories: download traffic and upload traffic. Download traffic accounted for approximately 97% of the total data exchange and comprised three main components: video, audio, and control data. In contrast, upload traffic was exclusively composed of control data. Both upload and download transmissions utilised the QUIC protocol to achieve efficient data exchange.

1) *Upload Traffic Analysis:* The upload traffic was analysed for two sample VR games, Contagion VR: Outbreak and Propagation VR, revealing similar characteristics. For Contagion VR: Outbreak, the observed upload data rates ranged from a minimum of 1.7 Mbps to a maximum of 3.5 Mbps, with an average rate of 3.4 Mbps. Propagation VR showed comparable performance, with a slightly lower minimum rate of 1.6 Mbps, a higher maximum rate of 3.7 Mbps, and an identical average of 3.4 Mbps. This uniformity in upload traffic suggests consistent control data requirements across the two games, irrespective of their individual gameplay dynamics. The most frequently observed upload packet size was 563 bytes. Given that upload traffic constitutes only 3% of the total data, the primary focus of this analysis will be on the download traffic.

2) *Download Traffic Analysis:* The download traffic of both VR games exhibited distinct patterns. The most frequent frame size (1082 bytes) corresponded to QUIC-protected traffic, carrying encrypted audio and video streams essential for gameplay. The average packet time delta was 0.01 ms for Contagion VR and 0.04 ms for Propagation VR, indicating more frequent packet transmissions and higher throughput in Contagion VR.

A comparison of download data rates showed consistently lower values for Propagation VR. Contagion VR recorded a minimum of 65.1 Mbps, a maximum of 251.9 Mbps, and an average of 156.3 Mbps, while Propagation VR had 56.9 Mbps, 188.8 Mbps, and 125.1 Mbps, respectively. These variations likely stem from differences in gameplay complexity, graphical fidelity, or interactive features, with Contagion VR demanding greater resources for detailed environments or higher-resolution streaming.

Traffic exchange used the QUIC protocol, with ports 10400 and 34083 for download and upload, respectively. QUIC messages included Initial, 0-RTT, Handshake, Retry, and Protected Payload, with core gameplay data encrypted post-handshake. This encryption ensures secure, uninterrupted data flow, maintaining the immersive VR experience.

Overall, Contagion VR's higher data rates and smaller time deltas suggest greater sensitivity to bandwidth and latency, highlighting its higher resource demands compared to Propagation VR.

IV. TRAFFIC MODELLING

To model the collected VR traffic, a number of probability distributions were fitted to quantify the underlying charac-

teristics of the dataset. Kullback–Leibler divergence (D_{KL}) was used as a metric to evaluate the goodness of fit between the datasets and the statistical distributions. The D_{KL} , also referred to as relative entropy or I-divergence, is a statistical measure that quantifies how one probability distribution P diverges from a reference probability distribution Q . Mathematically, it is expressed as follows [11]:

$$D_{KL}(P \parallel Q) = \sum_{x \in \mathcal{X}} P(x) \log \left(\frac{P(x)}{Q(x)} \right) \quad (1)$$

The D_{KL} equals zero when P and Q 's probability density functions are identical, signifying no divergence between the distributions.

A. Data Rate

Analysis of the PDFs for data rate curves from two VR games Figure 2 reveals asymmetric distributions with heavier left tails. We fit the empirical data rates to thirty-two statistical distributions, as detailed in Table II, and evaluated their D_{KL} . The generalised logistic distribution achieved the lowest D_{KL} for both games, indicating the best fit. Table II ranks the D_{KL} values, sorted from best to worst fit.

The PDF of the generalised logistic distribution is as follows [12]:

$$f(x) = \frac{\frac{b}{\sigma} e^{-\frac{(x-\theta)}{\sigma}}}{\left(1 + e^{-\frac{(x-\theta)}{\sigma}}\right)^{b+1}}, \quad b > 0, \sigma > 0, \theta \in \mathbb{R}, x \in \mathbb{R}. \quad (2)$$

The generalised logistic distribution is parametrised by three key elements: the location parameter (θ), the scale parameter (σ) and the shape parameter (b). The location parameter determines the central position of the distribution, shifting it along the x-axis without affecting its shape or scale. The scale parameter controls the spread of the distribution, with larger σ values resulting in a flatter and wider distribution, while smaller σ values compress it, making it narrower. The shape parameter governs the steepness of the distribution's tails, with larger b values producing lighter tails (fewer extreme values) and smaller b values yield heavier tails (more extreme values).

The fitted parameters for the Generalized Logistic Distribution of Contagion VR: Outbreak are as follows: $b=0.55$,

TABLE II: D_{KL} Values for Statistical Distributions Fitted to VR Game Data Rates

Propagation VR		Contagion VR: Outbreak	
Distribution	D_{KL}	Distribution	D_{KL}
Generalized logistic	0.0095	Generalized logistic	0.0489
Burr	0.0121	Generalized gamma	0.0582
Log-gamma	0.0273	Log-gamma	0.0590
Weibull	0.0301	Weibull	0.0591
T-distribution	0.0381	Beta	0.0601
Gumbel	0.0413	Generalized normal	0.0645
Generalized normal	0.0416	Laplace	0.0659
Logistic	0.0428	Logistic	0.0662
Laplace	0.0472	T-distribution	0.0681
Beta	0.0486	Normal	0.0681

$\theta=173.54$, and $\sigma=14.81$. For Propagation VR, the fitted parameters are $b=0.45$, $\theta=136.45$, and $\sigma=6.82$. These parameters will be used in Section V to regenerate data that is representative of VR traffic. Such models provide researchers and professionals with a robust method to simulate VR video traffic effectively.

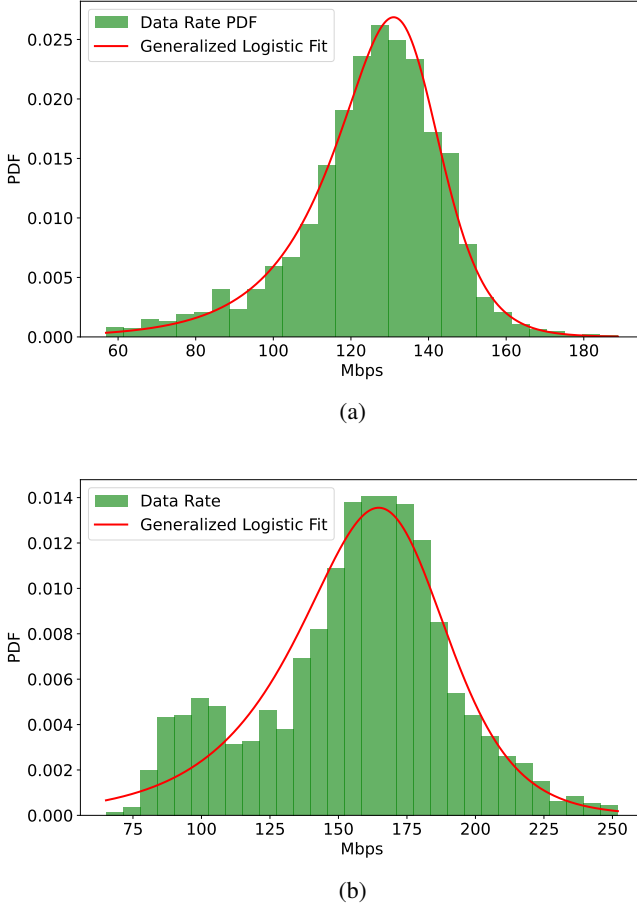


Fig. 2: Data rate and Generalised logistic distribution fittings for: (a) Propagation VR. (b) Contagion VR: Outbreak.

Algorithm 1 outlines the pseudocode for fitting data rates to probability distributions. The process starts by filtering the dataset to extract packets sent from the edge server to the HMD. These packets are then exported from Wireshark in CSV format. The final output is the best-fitting statistical distributions.

B. Inter-arrival Time (Time Delta)

In this study, the time difference between two consecutive frames, referred to as time delta in Wireshark, is equivalent to the commonly known Inter-arrival Time. We use these terms interchangeably throughout the paper. Our focus is on modelling the time delta for the download segment of VR traffic, specifically representing the data transmission from the edge server to the HMD.

The Probability Density Function of the inter-arrival time for both VR games exhibits symmetric pattern. Notably, the

distribution is characterised by the lack of a tail on the right side and a short tail on the left side, as illustrated in Figure 3. This distinctive behaviour highlights the unique temporal dynamics of VR game traffic, offering key insights into how packets are transmitted in these immersive environments. To

Algorithm 1 Empirical Data Rate Fitting

Require: Input Empirical Data from CSV file

Ensure: List of probability distributions sorted by D_{KL} best fit

- 1: **Function** Calculate $D_{KL}(p, q)$
- 2: Normalize p and q distributions
- 3: **return** $\sum p \log(p/q)$
- 4: **Function** Fit Distributions(Empirical Data)
- 5: Create histogram of empirical data
- 6: Define distributions to test
- 7: **for** each distribution **do**
- 8: Fit distribution parameters to empirical data
- 9: Calculate PDF for fitted distribution
- 10: Compute D_{KL} between histogram and PDF
- 11: Store results in dictionary
- 12: **end for**
- 13: **return** results and histogram
- 14: **Main Program**
- 15: Import and prepare data
- 16: results $\leftarrow$ Fit Distributions(Empirical Data)
- 17: Sort distributions by D_{KL} scores
- 18: Plot empirical data and fitted distributions
- 19: **return** sorted distribution results

model the inter-arrival time, we first exported a CSV file from Wireshark containing only the packets transmitted from the Edge Server to the HMD, along with their corresponding timestamps. The inter-arrival time was calculated by determining the difference between the timestamp of each frame and that of the previous frame. Subsequently, we employed the same methodology for fitting the data rate, by calculating the KL Divergence values to assess the fit of various probability distributions. Table III presents the D_{KL} results for both VR games, identifying the distributions most accurately representing their inter-arrival time data.

The results in Table III indicate that for Propagation VR, the Generalized Extreme Value (GEV) distribution achieved the lowest D_{KL} (0.1112), making it the most accurate model for the dataset. Similarly, for Contagion VR: Outbreak, the GEV distribution also performed best with a KL divergence of 0.0902. This consistency across both scenarios underscores the suitability of the GEV distribution for modelling VR traffic inter-arrival times. Furthermore, the fitted GEV parameters for the two VR games are remarkably similar, with Propagation VR characterised by Shape = -0.425194, Location = 0.005478, and Scale = 0.001389, and Contagion VR: Outbreak having Shape = -0.383505, Location = 0.005210, and Scale = 0.001732. These close parameter values reinforce the robustness of the GEV distribution for capturing the temporal behaviour of VR traffic.

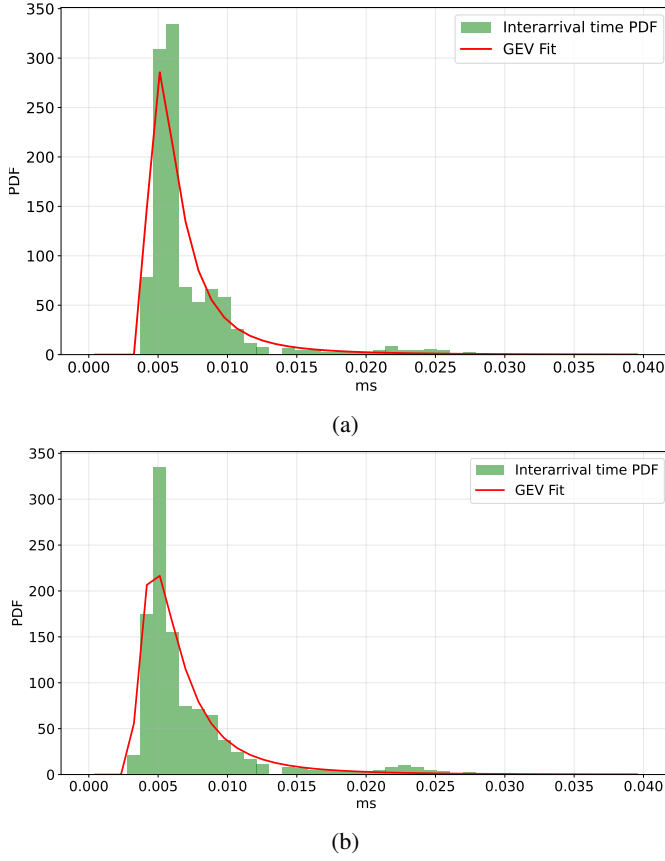


Fig. 3: PDF of inter-arrival time for: (a) Propagation VR. (b) Contagion VR: Outbreak.

TABLE III: KL Divergence Values for Statistical Distributions Fitted to VR Game Time delta

Propagation VR		Contagion VR: Outbreak	
Distribution	D_{KL}	Distribution	D_{KL}
GEV	0.1112	GEV	0.0902
Cauchy	0.1911	Burr	0.1238
Power-lognormal	0.1922	Cauchy	0.1941
T-distribution	0.2012	Lognormal	0.2209
Pareto	0.2727	Power-lognormal	0.2824
Exponential	0.2729	Generalized pareto	0.2950
Beta	0.3324	Erlang	0.2987
Generalized gamma	0.3423	Generalized normal	0.3069
Weibull-max	0.3533	Generalized gamma	0.3137
Generalized logistic	0.3534	Generalized logistic	0.3288

Three key parameters characterise the GEV distribution: μ (location), which defines the central tendency of the distribution; σ (scale), which determines the spread of the data; and ϵ (shape), which influences the tail behaviour. The general form of the GEV distribution is provided in Equation 3, as defined in [13]. Notably, when the shape parameter ϵ equals zero, the GEV represents the Gumbel distribution. For positive ϵ , it corresponds to the Fréchet distribution, while negative ϵ characterises the Weibull distribution. The slight differences in fitted parameters suggest that either set can be used to model the inter-arrival time of VR traffic effectively.

$$f(x) = \begin{cases} = \frac{1}{\sigma} e^{-(1+\epsilon(x-\mu)/\sigma)^{-\frac{1}{\epsilon}}} \{1 + \epsilon(\frac{x-\mu}{\sigma})\}^{-\frac{1}{\epsilon}-1}, & \text{for} \\ \epsilon < 0, -\infty < x \leq \mu - \frac{\sigma}{\epsilon} \\ \epsilon > 0, \mu - \frac{\sigma}{\epsilon} \leq x < \infty \\ = \frac{1}{\sigma} e^{-e^{-(x-\mu)/\sigma}} e^{-(x-\mu)/\sigma}, & \text{for} \\ \epsilon = 0, -\infty \leq x < \infty. \end{cases} \quad (3)$$

V. VR DATA REGENERATION AND MODEL VALIDATION

A. Data Rate Generation

Algorithm 2 outlines the process of generating VR traffic data rates (Mbps) using the Generalized Logistic distribution with fitted parameters. The generated and empirical data rates align well across key statistical metrics, except for a minor discrepancy in the minimum value, which is unlikely to affect network planning or resource allocation. Median, average, and standard deviation values closely match, confirming the model's accuracy in capturing data rate variability. The probability density function (PDF) of the generated data exhibits an asymmetric pattern with a heavier left tail, mirroring the empirical distribution. Table III summarises key metrics, including minimum, maximum, median, average, and standard deviation. While the generated maximum values slightly exceed empirical values—by 13% in the Contagion VR scenario—this overestimation ensures adequate network capacity, preventing resource underestimation.

B. Inter-arrival Time Generation and Validation

To generate the inter-arrival time (time delta) for VR traffic, we applied the same procedure and code as described in Algorithm 2, with the key difference being the use of the GEV distribution instead of the Generalized Logistic distribution. The GEV parameters, along with the required number of samples, were provided as inputs to the generation function. The generated inter-arrival times were then stored in a CSV file.

Table V compares the generated and empirical inter-arrival times for both VR scenarios. The peak's centre (median and average) and spread (standard deviation) closely match, highlighting the GEV distribution's accuracy in capturing VR inter-arrival times.

However, the generated distributions have heavier tails, with higher maximum values than the empirical data. Despite this,

TABLE IV: Comparison of Generated and Empirical Statistics for Data Rate

Unit (Mbps)	Propagation VR		Contagion VR: Outbreak	
	Empirical	Generated	Empirical	Generated
Minimum	1.261746	56.882408	6.091981	65.152056
Maximum	186.726125	188.784880	285.683727	251.987064
Median	127.292066	127.281716	159.289863	160.734904
Average	124.846398	125.1327475	156.108865	156.368502
std	18.551593	18.534895	34.532347	34.431353

Algorithm 2 Generation of Generalised Logistic Distribution Data Rate for VR Traffic

Require: Shape, Location, Scale parameters, Number of samples N

Ensure: Data Rate with N data points following generalised logistic distribution

- 1: **Function** Generate Logistic Data(shape, loc, scale, N)
 - 2: Initialize empty array data
 - 3: **while** length of data $< N$ **do**
 - 4: Generate samples using generalized logistic distribution
 - 5: Concatenate with existing data
 - 6: **end while**
 - 7: **return** Data Rate with generated data
 - 8: **Main Program**
 - 9: Set distribution parameters (shape=0.45, loc=136.45, scale=6.82)
 - 10: data $\leftarrow$ Generate Logistic Data(shape, loc, scale, $N=10000$)
 - 11: Save data to CSV file
 - 12: Plot distribution with theoretical curve
 - 13: Calculate and display basic statistics
-

TABLE V: Comparison of Generated and Empirical Statistics for Inter-arrival Time

Unit (ms)	Propagation VR		Contagion VR: Outbreak	
	Empirical	Generated	Empirical	Generated
Minimum	0	0.003373	0.001000	0.002472
Maximum	0.040000	0.107700	0.040000	0.104424
Median	0.006000	0.005994	0.006000	0.005848
Average	0.007265	0.007148	0.00736	0.007121
std	0.004179	0.004445	0.004880	0.004830

the GEV distribution effectively models VR inter-arrival times, capturing key characteristics and supporting further analysis.

VI. APPLICATIONS AND FUTURE WORKS

The proposed models for data rate and inter-arrival time have broad applications across multiple domains, offering significant potential for optimising network performance and user experience. In network infrastructure planning, Internet Service Providers (ISPs) and data centre operators can use these models to dimension networks and optimise infrastructure for handling VR traffic. A tailored resource allocation strategy can further balance VR traffic with other network loads, leveraging metrics like data rates and inter-frame time deltas to enhance resource utilisation. For Quality of Service (QoS) and Quality of Experience (QoE) management, the models enable the design of effective buffer management strategies and precise Service Level Agreements for VR applications, ensuring smoother traffic handling and consistent user satisfaction.

In the context of 5G/6G networks, the models support network slicing optimisation and capacity planning to accommodate growing VR traffic demands. They also facilitate the development of VR-specific network protocols, addressing the unique challenges of low-latency, high-bandwidth interactive

applications. Future work could extend these models to augmented reality (AR) and mixed reality (MR) applications, integrate machine learning for improved predictive accuracy, and explore cross-domain applications in healthcare, education, and industrial automation. By addressing current VR traffic challenges and enabling innovative solutions, these models contribute to the advancement of next-generation network technologies.

VII. CONCLUSION

This study presented a comprehensive traffic modelling framework for VR gaming applications, capturing the interplay between video, audio, and control data at an offline experimental setup with a high resolution and high frame rate. By utilising advanced statistical techniques, the proposed model accurately represents VR traffic patterns, enabling the generation of synthetic traces that align closely with real-world measurements. Our results demonstrate the effectiveness of generalised logistic and generalised extreme value distributions in modelling key traffic parameters such as data rate and inter-arrival time. The insights gained can inform the design of next-generation wireless networks, ensuring low latency and high throughput for immersive VR experiences.

REFERENCES

- [1] D. Cureton, "XR Market Growth." <https://www.xrtoday.com/virtual-reality/xr-market-growth-to-reach-333-billion-value-by-2025>. Accessed 13-Nov-2024.
- [2] IEEE, "Standard for head-mounted display (HMD)-based virtual reality (VR) sickness reduction technology," *IEEE Std 3079-2020*, pp. 1–74, 2021.
- [3] 3GPP, "3GPP TR 26.928 V18.0.0 (2023-03): 3rd generation partnership project; technical specification group services and system aspects; extended reality (XR) in 5G (release 18)," Technical Report TR 26.928 V18.0.0, 3rd Generation Partnership Project (3GPP), Mar. 2023.
- [4] S. Zhao, H. Abou-zeid, R. Atawia, Y. S. K. Manjunath, A. B. Sediq, and X.-P. Zhang, "Virtual reality gaming on the cloud: A reality check," in *Proc. Global Communications Conference (GLOBECOM)*, pp. 1–6, IEEE, 2021.
- [5] M. Lecci, A. Zanella, and M. Zorzi, "An ns-3 implementation of a bursty traffic framework for virtual reality sources," in *Proc. of the Workshop on ns-3*, pp. 73–80, 2021.
- [6] M. Lecci, M. Drago, A. Zanella, and M. Zorzi, "An open framework for analyzing and modeling XR network traffic," *IEEE Access*, vol. 9, pp. 129782–129795, 2021.
- [7] J. Färber, "Network game traffic modelling," in *Proc. of the 1st workshop on Network and system support for games*, pp. 53–57, 2002.
- [8] A. Alhilal, K. Shatilov, G. Tyson, T. Braud, and P. Hui, "Network traffic in the metaverse: The case of social VR," in *Proc. 43rd International Conference on Distributed Computing Systems Workshops (ICDCSW)*, pp. 109–114, IEEE, 2023.
- [9] NVIDIA, "NVIDIA Video Codec SDK." <https://developer.nvidia.com/video-codec-sdk>, 2024. [Accessed 13-Nov-2024].
- [10] Y. Chen, H. Shi, Q. Weng, and Z. Shi, "Congestion control design of multicast quic based on reinforcement learning," in *Proc. International Conference on Ubiquitous Communication (Ucom)*, pp. 232–236, IEEE, 2023.
- [11] G. Wang, Z. Sun, T. Wang, Y. Li, and H. Hu, "Finding influential nodes in complex networks based on kullback–leibler model within the neighborhood," *Scientific Reports*, vol. 14, no. 1, p. 13269, 2024.
- [12] K. Abberger, "ML-estimation in the location-scale-shape model of the generalized logistic distribution," tech. rep., CoFE Discussion Paper, 2002.
- [13] S. Kotz and S. Nadarajah, *Extreme value distributions: theory and applications*. world scientific, 2000.