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Estimating Quality of Experience in Multicast Point Cloud Streaming over 5G Networks

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Abstract—**This paper proposes three Quality of Experience (QoE) prediction models tailored for multicast point cloud (PC) streaming, leveraging the Open Radio Access Network (O-RAN) framework for facilitating data sharing between Over-The-Top (OTT) providers and Mobile Network Operators (MNOs). The first model, called *Network-only*, is based on machine learning algorithms (ML) to capture the relationship between diverse 5G network parameters and the corresponding PC quality estimated using a state-of-the-art No-Reference (NR) PC quality assessment (PCQA) metric. The other two models (*Network+PCCI* and *Network+Distortion*) are trained with the same network features plus additional PC data, namely, the proposed point cloud complexity index (PCCI) and the distortion type, respectively. The PCCI is an original metric that categorizes PCs based on their inherent complexity characteristics. The achieved results demonstrate that the proposed PCCI enables the *Network+PCCI* QoE model to achieve a higher Pearson linear correlation coefficient (PLCC) (0.941 vs. 0.809 vs. 0.612) and a lower root mean square error (RMSE) (0.174 vs. 0.268 vs. 0.509) compared to *Network+Distortion* and *Network-only* QoE models, respectively.**

Index Terms—**Point cloud streaming, Quality of Experience (QoE), 5G, Machine Learning, Point Cloud Complexity Index.**

I. INTRODUCTION

With the advent of 5G networks, immersive applications, e.g., Virtual Reality (VR) and Augmented Reality (AR), have become increasingly feasible and integrated into everyday applications, such as video conferencing, live entertainment, and virtual events. Point clouds (PCs) are one of the main enablers of these immersive applications because they provide a realistic 3D representation of static and dynamic objects, environments, and human subjects [1]. Novel protocols based on Dynamic Adaptive Streaming over HTTP (DASH) have been investigated to support the adaptive streaming of PC sequences from the server to the client side [2]. However, the real-time delivery of PC contents over 5G networks presents significant challenges to guarantee satisfactory Quality of Experience (QoE) for the end users. In this regard, objective no-reference (NR) point cloud quality assessment (PCQA) methods play a crucial role, since they can estimate the PC quality, solely based on the analysis of the received (distorted) PC, to drive optimal rate adaptation strategies [3].

However, the only entity at the client side with access to the distorted PC is the over-the-top (OTT) application provider, which can accurately estimate the QoE using NR PCQA methods. On the other hand, mobile network operators (MNOs) face significant challenges in estimating end users' QoE because they can only measure network-related parameters (e.g., throughput), but do not have any information on application-level metrics. While Quality of Service (QoS) metrics have been typically used to estimate the perceived QoE, the accelerated growth of diverse end devices and advanced immersive multimedia streaming scenarios has increased the limitations of traditional QoS-to-QoE methods [4].

The utilization of machine learning (ML) has brought new possibilities for MNOs, which have started to train ML algorithms on the available data concerning network-related measurements and using as the label (the variable to be predicted) the corresponding QoE, estimated with application-layer QoE objective models. As a result, the trained ML models can estimate the end user's QoE without knowledge of application data, but only based on the monitored network status. This approach has been used to predict the QoE of gaming [5] and video streaming [6] applications.

In this paper, we propose three ML-based QoE prediction models for multicast PC streaming over 5G networks. The proposed solutions rely on a collaboration between MNO and OTT, where the OTT shares QoE estimations of distorted PCs at the user side and optional PC-related data. The first model, called *Network-only*, captures the relationship between several 5G network parameters and the corresponding QoE, which has been estimated using the state-of-the-art MS-PCQE NR PCQA metric [7]. The other two models (*Network+PCCI* and *Network+Distortion*) are trained with the same network features plus additional PC data, namely, the proposed point cloud complexity index (PCCI) and the distortion type, respectively. We have implemented the three QoE prediction

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models using different linear and non-linear ML algorithms, and we have compared the achieved performance in terms of QoE prediction errors and correlation coefficients. The achieved results demonstrate that the *Network+PCCI* QoE model achieves the best prediction performance, thanks to the contribution provided by the knowledge of PCCI, which captures intrinsic differences between PCs.

The paper is structured as follows. Section II discusses the related work. In Section III, we present the proposed solution, whereas Section IV introduces the considered experimental scenario. The results are discussed in Section V, and, finally, Section VI concludes the paper.

II. RELATED WORK

A. QoE Assessment of PCs

PCs typically consist of a huge number of points to accurately represent complex 3D scenes with high quality, resulting in large-sized media content. Compression techniques are then used to reduce the data size of PCs before streaming. However, while compression aims to preserve as much as possible of the original PC, it is a lossy process that may lead to diverse types of distortions in the reconstructed PC. To understand the trade-off between PC compression techniques and perceived quality, Lazzarotto et al. explored various compression algorithms and their impact on QoE [8]. Furthermore, Javaheri et al. examined the effects of PC rendering and encoding on the perceived subjective and objective quality [9].

Recently, significant progress has been made on objective PCQA techniques, which are mathematical algorithms used to estimate the quality of the reconstructed PCs. These methods can be classified into full-reference (FR), reduced-reference (RR), and NR based on the extent of reference PC data utilized to compute the quality metric. The survey in [3] provides an overview and a comparison of NR PCQA metrics, which can be used in real-time systems because they evaluate the PC quality without requiring original reference data. Among these methods, the NR MS-PCQE approach proposed by Chai and Shao in [7] has demonstrated the best performance in predicting the QoE of PCs across state-of-the-art datasets, such as LS-PCQA [10] and SJTU-PCQA [11]. The MS-PCQE leverages a multi-scale interaction and multi-focal length feature modelling, which can deal with quality estimation of PCs affected by different distortion types and intensity levels.

While these studies have advanced the understanding of PC quality, there remains a gap in integrating these metrics into QoE-aware management frameworks, particularly for dynamic multicast PC streaming scenarios.

B. QoE-aware Management of 5G networks

State-of-the-art resource management approaches for 5G networks are typically QoS-based, i.e., they map different values of channel quality indicator (CQI) into diverse levels of QoS requirements in terms of network parameters, such as throughput, latency, and packet loss, to satisfy the application requirements at the user end side [12]. However, the accelerated growth of diverse end devices and advanced immersive multimedia streaming scenarios has increased the limitations of traditional QoS-to-QoE methods, by opening the doors to novel QoE-aware management approaches [4]. To overcome the lack of knowledge of the MNOs concerning application and content-related data, which is of fundamental importance to accurately estimate the user's QoE, some approaches have been proposed focused on training ML algorithms on network-related data and using the QoE estimated at the application side as the ground-truth data, i.e., the variable to be predicted. This approach has been used to predict the QoE of gaming [5] and video streaming [6], [13] applications using ML models trained on network-related data. However, in [5], no details of the training and deployment of the ML model in the 5G infrastructure are provided, whereas the studies in [6] and [13] have only considered the streaming of high-definition videos, limiting the potentialities of the 5G network. To move forward, in this paper, we exploit the full potential of 5G networks by proposing different ML-based QoE prediction models for PC streaming, which requires a large amount of bandwidth.

III. PROPOSED SOLUTION

A. Architecture

We propose three ML-based QoE prediction models for multicast PC streaming over 5G networks. The proposed solutions rely on a collaboration between MNO and OTT, where the OTT shares QoE estimations of distorted PCs at the user side and optional PC-related data.

The MNO leverages the O-RAN architecture to exchange data with the OTT through RESTful APIs, as shown in Fig. 1. This collaboration aims to prevail over the MNO's lack of knowledge concerning the application's parameters, which, in this case, is a PC streaming application. Thus, the OTT utilizes an objective QoE model to predict the quality of the distorted PC at the user side and then shares this information with the MNO, together with PC-related data. The MNO trains ML algorithms on the available data concerning network-related measurements and optional PC-related data, using the corresponding QoE prediction provided by the OTT as the label, i.e., the variable to be predicted. The trained ML models can then be used to implement a QoE-aware management of the network resources to optimize the PC streaming to the end users. The OTT would also benefit from this collaboration because a satisfied user is less likely to become a churner.

The O-RAN framework provides an ideal environment for QoE-aware optimization through its disaggregated and flexible elements. Within this framework, two key components are utilized: the Non-Real Time (Non-RT) and Near-Real Time (Near-RT) RAN Intelligent Controllers (RICs). The Non-RT RIC is a module of the Service Management and Orchestration (SMO) and serves as the long-term orchestration and policy management layer. It gathers network metrics (e.g, SINR, CQI, throughput) from the O-RAN Central Unit and Distributed Unit (O-CU/O-DU) components. Additionally, it receives QoE estimations and PC-related data from the OTT through RESTful APIs. These network and application-related data are preprocessed and used for training ML-based QoE

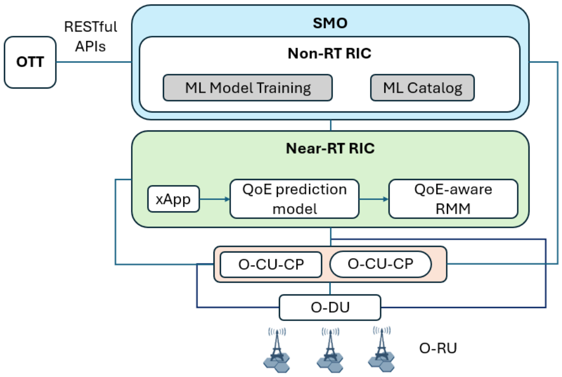

Fig. 1: Architecture of the proposed solution.

prediction models, which are periodically updated and stored in the ML Catalog for deployment.

The Near-RT RIC hosts the xApps, i.e., specific microservices running the ML models provided by the Non-RT RIC to perform QoE predictions. These xApps utilize instantaneous network information collected from the O-CU/O-DU entities, along with the application-layer data provided by the OTT, to perform real-time QoE predictions. These predictions are used to drive resource allocation decisions through the QoE-aware Radio Resource Management (RRM) module, whose management actions are implemented at the Radio Units (RU) level to optimize the QoE perceived at the user end. This creates a feedback loop where data collection, modelling, inference and optimization continuously improve the QoE prediction capabilities of the framework.

B. QoE Prediction Models

The proposed solution aims to train an ML-based model that can accurately estimate the end user's QoE solely based on the monitored network-related data. This model would enable the MNO to independently manage the network resources without needing application-related data. We refer to this approach as the *Network-only QoE model*.

However, it is well-known that the QoE is influenced by several factors, including application and content-related distortions, which are not related to changes in the network state. This means that even when the network provides a high QoS, the end user may perceive a low QoE. For this reason, we have considered two additional QoE prediction models that, besides network-related data, also include application-related data in the model training process. One model includes the PCCI, a metric we have defined to group PCs with similar intrinsic characteristics. Another model includes the type of distortion affecting the PC as additional information for training. In the following, we refer to these models as the *Network+PCCI QoE model* and the *Network+Distortion QoE model*, respectively.

C. Hybrid QoE Prediction Framework

The inclusion of application-related data to train the QoE prediction models (*Network+PCCI* and *Network+Distortion*) requires an exchange of information between the MNO and the OTT. To this aim, the proposed hybrid QoE prediction framework operates through a two-step process that minimizes overhead while maximizing QoE prediction accuracy.

In the first step, the OTT provider shares the application-related data (either the PCCI or the distortion information) with the MNO through the established RESTful API at the beginning of the streaming session. The shared data is provided once per PC or scene and remains valid throughout the entire streaming session, ensuring minimal transmission overhead.

In the second step, the Near-RT RIC utilizes the shared information to select the appropriate specialized ML model from those stored in the ML Catalog within the Non-RT RIC. Each model is specifically trained for a particular complexity category or PC distortion, establishing targeted relationships between network parameters and QoE for PCs with similar intrinsic characteristics. Once the appropriate model is selected, it is applied to real-time network parameters (CQI, SINR, throughput) collected from the O-CU/O-DU entities to predict the QoE. The predicted values then inform resource allocation decisions through the QoE-aware RRM module, enabling the network to dynamically optimize resource distribution based on both content complexity and network conditions.

IV. EXPERIMENTAL SCENARIO

This section describes the experimental scenario to test the performance of the proposed solution. Section IV-A introduces the considered 5G network environment. In Section IV-B, we discuss the selected LS-PCQA dataset, while the NR MS-PCQE metric that we used to estimate the QoE of the selected distorted PC samples is presented in Section IV-C. Finally, Section IV-D defines the proposed PC complexity index.

A. 5G Network Environment

We assume a 5G deployment, including a set of B New Radio Base Stations (BSs) providing a channel bandwidth W with N physical Resource Blocks (RBs). An RB is defined as the smallest frequency unit that a base station can allocate, consisting of 12 contiguous subcarriers with uniform spacing. The bandwidth of an RB is calculated as $W_n = 12 \times \Delta f$, where the subcarrier spacing Δf is expressed in kHz and follows the relationship $\Delta f = 15 \times 2^{\mu}$. Here, μ represents the numerology as defined by the 5G NR specifications.

Based on CQI and SINR reports collected from the end user devices, the BSs dynamically assign RBs and determine suitable modulation and coding schemes. To compute the throughput for the end users, the system maps the CQI values from simulation outputs to Modulation and Coding Schemes (MCS) using the 3GPP CQI-to-MCS lookup tables outlined in TS 38.214 [14]. By integrating MCS data, the number of assigned resources, and Transport Block Size (TBS) values, the throughput for a given user u, denoted as Th_u, is derived while accounting for retransmissions and protocol overhead. This throughput is expressed as $Th_u = n_u^{\text{used}} \times W_n \times eff_u$, where n_u^{used} is the number of RBs allocated to user u, W_n is the bandwidth per RB, and eff_u corresponds to the spectral efficiency determined by the user's channel conditions.

B. PCQA Dataset

To ensure robustness and generalizability of the proposed QoE prediction models, the Large-scale Point Cloud Quality Assessment Dataset (LS-PCQA) was employed [10], which represents one of the most comprehensive benchmarks available for PCQA. This dataset comprises 104 reference PCs, each subjected to 31 distinct types of distortions across 7 severity distortion levels, for a total of more than 22,000 degraded PC samples. The impairments encompass a diverse range of alterations, including various compression methods, color and attribute distortions, geometry alterations, noise and downsampling distortions. However, our research focuses exclusively on transmission-induced quality impairments, as they directly relate to network conditions in multicast PC streaming scenarios. Consequently, generic noise, color/attribute alterations and geometric shifting distortions were deliberately excluded from the modelling considerations, as these primarily represent artifacts introduced during PC acquisition or initial processing stages rather than during network transmission. Instead, the focus was on compression and downsampling method distortions, which directly correlate with network transmission constraints and produce measurable changes in PC size, establishing a more direct relationship between network parameters, PC complexity and perceived quality.

C. NR PCQA metric

To estimate the QoE evaluation of the distorted PC samples considered from the LS-PCQA dataset, we employed the NR MS-PCQE metric in [7], which demonstrated state-of-the-art performance in PCQA by leveraging multi-scale interaction and multi-focal length feature modelling. Moreover, this approach aligns with our objective of developing a QoE prediction model that does not require access to reference PCs.

We have employed the Python implementation of the MS-PCQE metric in [15]. This code estimates the PC quality by first generating twelve projection images, mapping the PC onto six orthogonal planes (front, back, left, right, top, and bottom) at two distinct focal lengths, $0.6R$ and $0.4R$, where R represents the radius of the PC's bounding sphere. Each projection is standardized to a 512×512 pixel resolution to ensure consistent feature extraction. These projections are then processed through a feature extraction pipeline consisting of a ResNet-18 backbone, which provides robust visual feature representation capabilities while maintaining computational efficiency. The extracted features are further refined through ConvGRU modules that model multi-scale spatial relationships within each projection. A dual-branch transformer architecture then captures global features with attention mechanisms specifically tuned to perceptually relevant regions. This approach enables the model to prioritize areas with higher visual significance, mirroring human visual perception patterns. Finally, these multi-dimensional features are aggregated through a quality-aware evaluator to yield a single comprehensive quality score for each PC, effectively estimating the user-perceived QoE in terms of the predicted Mean Opinion Score (MOS), ranging from 1 (lowest quality) to 5 (highest quality).

D. Point Cloud Complexity Index

The PCCI represents an important contribution to categorising PCs based on their intrinsic properties that influence perceptual quality. Indeed, the QoE estimation of the considered distorted PCs revealed an important pattern that significantly impacts network-based QoE prediction: PCs of similar size often exhibit drastically different MOS values. For example, among PCs of approximately 5 MB, the predicted MOS can assume values between 2 (poor quality) and 4 (good quality). This highlights a fundamental limitation in relying solely on network parameters for QoE prediction, as PCs requiring similar throughput for transmission can produce vastly different perceptual quality outcomes. Further examination of the dataset demonstrated that degraded PCs derived from the same original PC exhibit consistent MOS-to-size relationships. Additionally, degraded PCs from different originals but with similar characteristics show comparable MOS-to-size patterns. The inherent properties of the original PCs significantly influence how changes in size affect perceived quality. The impact of size reduction on a complex human figure differs significantly from that on a simple geometric shape, even when the throughput requirements are identical.

These findings underscore the necessity of the proposed PCCI, which captures these intrinsic differences between PCs, and it is aimed at enabling more accurate QoE prediction models. By categorizing PCs based on their complexity characteristics, the concept of specialized models is introduced, which accounts for the variations in quality perception that cannot be explained by network parameters alone. This methodological refinement ensures the QoE prediction framework addresses the fundamental relationship between content complexity, network conditions and perceived quality in multicast PC streaming scenarios.

The PCCI is derived from a comprehensive analysis of several key characteristics of the original PCs. Among these are the original file size, spatial metrics like number of points, three-dimensional bounding box measurements, volume, point density, and height variation. Additionally, distribution properties (centroid, mean, and median coordinates), along with standard deviations across all dimensions, were examined. The shape descriptors covered the eigenvalues, along with derived measures that included linearity, planarity, and scattering. Convex hull metrics and surface-to-volume ratios were incorporated as well. Finally, statistical characteristics were considered, such as dimensional skewness (asymmetry), kurtosis (peakedness), nearest neighbor distances, and point-to-volume ratios. This multifaceted approach enabled the capture of the full spectrum of geometric complexity and spatial characteristics inherent in each PC.

Using these metrics, unsupervised clustering techniques were applied to categorize the PCs into distinct complexity classes. For the distorted PCs selected from the LS-PCQA dataset, it was determined that they could be effectively grouped into three complexity categories based on their intrinsic geometric and structural properties. Figure 2 illustrates

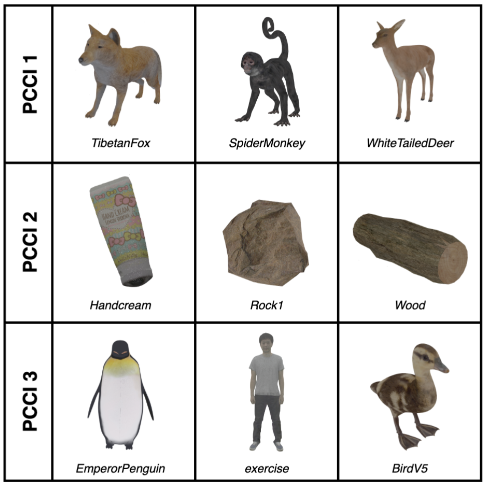

Fig. 2: Examples of sample PCs classified in 3 different PCCI.

three representative examples of PCs for each PCCI, illustrating the perceptible differences in spatial and geometric characteristics across the categories.

V. RESULTS

A. Test Setup

The LLSim5G simulator [16] was used to implement the 5G network scenario in Section IV. This environment enables fine-grained control over network parameters while accurately representing multicast PC streaming across two device types: mobile (MO) and static (ST), each with different mobility patterns and reception capabilities. The experiment included 8 total devices (3 MO and 5 ST). Dynamic PC streaming was simulated at a fixed frame rate using the static PC dataset described in Section IV-B. Given the substantial resource requirements of PC streaming services, which can demand throughput ranging from tens to thousands of Mbps, simulation parameters were configured to reflect the specialized nature of this service. Users were modeled with reception conditions yielding CQI values predominantly in the higher range of the spectrum, representing the minimum viable conditions for immersive PC applications. To ensure statistical significance, 30 simulation runs were conducted under the specified conditions, achieving a 95% confidence value in the results.

At the initialization of each simulation, users were assigned a fixed PCCI value that remained constant throughout the session, reflecting the consistency of content complexity within typical immersive experiences. This approach aligns with the methodology described in Section III. For each user at each time sample, the following network parameters were extracted: block error rate (BLER), SINR, CQI, distance to the assigned BS, speed, number of allocated resource blocks (n_u^{used}) and throughput (Th_u). Based on the available throughput and the assigned PCCI, a specific PC with its corresponding predicted MOS value was selected for each user at each moment. Table I summarizes the key simulation parameters used in the experimental scenario for model training and evaluation.

TABLE I: Simulation parameters.

Parameter	**Value**
Number of users	8
Simulation time / Time resolution	60 s / 1 s
PC Frame rate	15 fps
Grid size	200 m × 200 m
Number of BSs / Height of BS	4 / 10 m
BS type	Urban Micro Station
BS operating frequency / μ	28 GHz / 3
BS Bandwidth, W	400 MHz
RB's bandwidth, W_n	1.44 MHz
Subcarrier spacing	120 kHz
Transmission power BS	26 dBm
Antenna gain BS	10 dBi
Power spectral density of noise	-174 dBm/Hz
Type of end devices	MO, ST
Mobility model MO / ST	Random directional/static
MO speed	0 – 0.8 m/s

TABLE II: Performance metrics for different QoE models.

(a) ***Network-only***

Metric	Linear Models	KNNR	RFR	SVR	GBR	SMLP
RMSE	0.546	0.533	0.512	0.534	**0.509**	0.519
MAE	0.464	0.440	**0.416**	0.427	0.417	0.431
R^2	0.278	0.312	0.367	0.311	**0.374**	0.348
PLCC	0.528	0.559	0.607	0.571	**0.612**	0.593
SRCC	0.505	0.502	0.541	0.504	**0.544**	0.526

(b) ***Network+PCCI***

Metric	Linear Models	KNNR	RFR	SVR	GBR	SMLP
RMSE	0.284	0.227	0.177	0.219	**0.174**	0.205
MAE	0.213	0.170	**0.121**	0.173	0.127	0.155
R^2	0.673	0.801	0.881	0.816	**0.885**	0.838
PLCC	0.818	0.896	0.939	0.904	**0.941**	0.915
SRCC	0.813	0.863	0.901	0.853	**0.904**	0.869

(c) ***Network+Distortion***

Metric	Linear Models	KNNR	RFR	SVR	GBR	SMLP
RMSE	0.325	0.312	**0.268**	0.313	0.291	0.298
MAE	0.258	0.243	**0.187**	0.234	0.216	0.237
R^2	0.576	0.598	**0.681**	0.594	0.581	0.628
PLCC	0.735 - 0.736	0.749	**0.809**	0.756	0.738	0.774
SRCC	0.722 - 0.724	0.717	**0.778**	0.728	0.705	0.745

Following dataset generation, nine ML regression methods were implemented and evaluated: Linear Regression (LiR), Ridge Regression (RR), Lasso Regression (LaR), Elastic Net Regression (ENR), Support Vector Regression (SVR), Random Forest Regression (RFR), Gradient Boosting Regression (GBR), K-Nearest Neighbors Regressor (KNNR) and a Shallow Multilayer Perceptron (SMLP). The dataset was split with 80% allocated for training and 20% for testing. After a comparative analysis of various scaling techniques, StandardScaler provided the best overall performance across all ML models and was consequently applied throughout the analysis. Using the complete feature set, the best hyperparameters for each method were identified through grid search with 5-fold cross-validation. These ML models were used to implement the three QoE prediction models presented in Section III: i) *Network-only*, solely trained on the aforementioned network parameters computed for each user; ii) *Network+PCCI*, trained using network parameters and the PCCI; and iii) *Network+Distortion*, trained using network and distortion information.

B. Results

Table II summarizes the performance of the three proposed QoE prediction models in terms of root mean squared error (RMSE), mean absolute error (MAE), coefficient of determination (R^2), Pearson linear correlation coefficient (PLCC) and Spearman rank correlation coefficient (SRCC). Note that "Linear Models" groups the results of the 4 linear regressors (LiR, RR, LaR, ENR), as they achieve comparable performance.

The *Network-only* QoE model achieved the lowest performance results. This was predictable since this model only utilizes network parameters to estimate the QoE without any kind of additional information concerning the PC. The best-performing ML algorithm for this model is the GBR, achieving an R^2 of 0.374, i.e., merely 37.4% of the variance in MOS values is explained by the model. This confirms our hypothesis that treating all PC data uniformly is insufficient for accurate quality prediction. The *Network+PCCI* QoE model demonstrates a substantial improvement in prediction performance. These results are average metrics calculated across the three complexity categories, with each category having its trained model. The R^2 scores increase dramatically across all ML algorithms, with RFR and GBR achieving values of 0.881 and 0.885, respectively, more than a twofold improvement compared to the *Network-only* approach. GBR also achieved a remarkable 65.8% reduction in RMSE, from 0.509 to 0.174. Overall, the *Network+PCCI* QoE model exhibits substantially lower error metrics and higher correlation coefficients, exceeding 0.9 for tree-based models. These results further confirm the relevance of the PCCI knowledge to reduce the prediction error of the MOS for different PCs.

Finally, the *Network+Distortion* QoE model achieved intermediate performance compared to the two aforementioned models. These results are the average metrics across five distinct distortion types, each with its trained model. The best-performing ML algorithm for this model is RFR, achieving an R^2 score of 0.681 and followed by SMLP with 0.628. The former also achieved an RMSE of 0.268 and a PLCC of 0.809, which demonstrates that the knowledge of the distortion type affecting the PC can enhance QoE prediction performance. However, the RMSE achieved by the *Network+PCCI* using GBR is 0.174, which is 35.1% lower, resulting in the best QoE prediction model among those considered in this study.

Across all considered ML algorithms, linear regressors achieved the lowest performance metrics for each model, suggesting the relationship between trained features and the perceived QoE to be inherently non-linear. Among the non-linear models, SVR and KNNR generally yield the poorest results, although they still outperform the linear models. The SMLP achieved intermediate performance, demonstrating better capability to capture the non-linear relationships in the data, but falling short of the ensemble methods. RFR and GBR emerge as the top-performing approaches across all scenarios, with GBR slightly outperforming RFR when PCCI is considered. These tree-based algorithms excel at capturing the complex relationships between network parameters and perceived quality in PC streaming.

VI. CONCLUSIONS

We proposed and compared the performance of three ML-based QoE prediction models for multicast PC streaming over 5G networks. By training ML algorithms using only network parameters to estimate the QoE, the *Network-only* model achieved the lowest performance results. On the other hand, by also including PC-related data in the training process, the *Network+Distortion* and *Network+PCCI* models achieved better QoE prediction results. In particular, the inclusion of the proposed PCCI, which captures intrinsic differences between PCs, allows to achieve a twofold improvement compared to the *Network-only* model in terms of R^2, and an RMSE 35% lower than that achieved by the *Network+Distortion* model. In future work, we aim to test the performance of the proposed models on further PCQA datasets to ensure broader generalizability across diverse PC types and distortion scenarios.

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