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QoE-aware ML models based on network parameters for video streaming over 5G O-RAN architecture

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***Abstract*—This work proposes a machine learning (ML) based solution for enabling mobile network operators (MNOs) to estimate the quality of experience (QoE) provided during a video session just from the network's side data. The proposed ML model inserted into the 5G Open Radio Access Network (O-RAN) enables addressing multiple end devices (EDs) with a QoE-aware resource allocation without leveraging on the Service Provider (SPs) for the QoE estimation. We assume that the SP and the MNO cooperate during the training process, labeling the network-based collected dataset. The resulting ML model estimates the average QoE during the overall session time, which is influenced by the EDs' mobility behavior, the user channel quality variations, and available network resources. The proposal introduces a unified tool for addressing fixed and mobile EDs requesting videos with resolutions up to 4K and frame rates up to 60 fps. Multiple supervised ML regression models were trained and tested, where Gradient Boosting (GB) achieved the highest QoE estimation performance ($R^2 = 0.986$, $RMSE = 0.091$).**

***Index Terms*—5G, Machine Learning, O-RAN, Quality of Experience, Video Streaming**

I. INTRODUCTION

The fifth-generation (5G) wireless networks and beyond will open the doors to immersive and high-quality multimedia services. When dealing with such advanced applications, a purely network-centric approach will only partially capture the real user experience, mainly focusing on the network conditions and available resources. These strategies focus on network metrics to optimize the Quality of Service (QoS), disconnected from subjective expectations and the individual user experience [1]. Consequently, the optimization strategies must shift towards a more holistic user-centric approach that prioritizes Quality of Experience (QoE) while optimizing network resource usage and the overall QoS.

The QoE depends upon many influence factors, including system, human, and context factors [2]. However, it is widely recognized that without access to application-layer parameters on the service providers' (SPs) side, mobile network operators (MNOs) face significant challenges in accurately estimating customers' QoE. While MNOs can measure and control network-related parameters such as throughput and delay, SPs are limited to assessing application-level metrics, like video resolution. On the other hand, due to the accelerated growth of diverse end devices (EDs), network scenarios, and multimedia streaming services, the complexity of QoE assessment has increased, evidencing the limitations of traditional QoE methods.

To handle this, recent QoE modeling research efforts have been Machine Learning (ML) driven to provide a dynamic and real-time optimization loop for addressing actual and envisioned streaming applications. ML allows for modeling complex problems, such as quantifying the correlation between QoS and QoE, with high accuracy. However, selecting the most suitable ML model for each multimedia application remains an ongoing research challenge [3]. Furthermore, objective QoE models have been employed to estimate the ED's QoE using measured QoS parameters for addressing the correlation between QoS and QoE [4], [5].

The authors of [4] used supervised ML regression models for the QoE estimation of video-on-demand (VoD) services based on network parameters. They employed the P.1203.1 mode 0 (bitstream-based no-reference) model as the ground-truth QoE. The authors assumed that the Network Data Analytics Function (NWDAF) element (from the 5G core) collects the needed network data for ML training. Similarly, Miranda *et al.* [5] trained a decision tree model for QoE prediction using network parameters such as round-trip time (RTT), jitter, and packet loss rate between the VoD server and the clients. The ground-truth QoE values were derived using the P.1203.1

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mode 3 (full bitstream) model. The proposals in [4] and [5] focused exclusively on predicting QoE using network-related parameters. However, these models were limited to H.264 encoded videos with resolutions up to full high definition (FHD) and frame rates up to 30 fps. Consequently, the video bitrates were restricted to ranges of 0.5–3 Mbps in [4] and 0.2–12 Mbps in [5], which constrained their applicability to advanced multimedia applications within the 5G network environment and beyond.

In [7], a Multi-layer Perceptron (MLP) model is proposed for estimating QoE in live video streaming scenarios. The input features include video resolution, screen size, performance type, network bandwidth, and RTT. Ground-truth QoE values are derived using a non-standardized objective model incorporating factors like video source quality. While the MLP model demonstrates high accuracy in predicting QoE, it was trained based on application parameters (i.e., video resolution, screen size) generally unavailable to the MNO. Additionally, how SP provides these features was not discussed. Considering the previous analysis, our proposal assumes that MNO and SP cooperate in training an ML model to estimate the QoE when tracking multiple EDs requesting VoD service. The proposed solution enables the prediction of the QoE of multiple EDs with different display resolutions and mobility patterns. They can play videos with resolutions of up to 4K and frame rates of up to 60 fps while leveraging the advanced capabilities of 5G networks. The ML model estimates the average QoE during a video session, influenced by the EDs' mobility behavior, the channel environment (e.g., channel quality conditions vary continuously over time), and available network resources. The rationale behind enabling the MNO capability to estimate the average QoE is to unlock the resources management with a QoE-aware fashion. Compared with previous works, we provide an ML-based solution only based on network's side data. Finally, unlike works [4], [5], [7], we propose integrating the model into the 5G Open Radio Access Network (O-RAN) framework, a flexible and disaggregated architecture recently gaining momentum [8], [9].

The remainder of the paper is structured as follows. Section II provides an overview of the proposed solution, the system model and the insertion into the O-RAN framework. Section III describes the followed methodology, detailing data collection and preparation. Then, Section IV discusses the ML training/testing results. Finally, Section V concludes the paper.

II. OVERVIEW OF THE PROPOSED SOLUTION

In this section, we illustrate the system model and provide an overview of the proposed ML-based prediction model inserted into the O-RAN framework.

A. System model

For modeling our desired scenario, we assume a 5G network deployment, including a set of B new radio (NR) base stations (BSs) defined by $\mathbb{B}$, with the sub-index $b \in \{1, 2, \ldots, B\}$. A channel bandwidth W (expressed in MHz) is considered over an operating frequency f and embracing N physical resource blocks (RBs). The RB bandwidth is $W_0 = 12 \times \Delta f$, where 12 represents the number of subcarriers and Δf is the subcarrier spacing (expressed in kHz). $\Delta f = 15 \times 2^{\mu}$, and μ is 5G NR numerology according to the standard.

We assume a set of U EDs requesting VoD services and denoted by $\mathbb{U}$ with the sub-index $u \in \{1, 2, \ldots, U\}$. Four types of EDs were recreated and randomly distributed in the service area: mobile (MO), tablet (TA), computer (PC), and TV. A binary variable, defined by $\nu_u \in \{0, 1\}$, defines the mobility or not of the EDs, where $\nu_u = 0$ identifies the static EDs and $\nu_u = 1$ the EDs under a random directional mobility behavior. The TVs and PCs are always static, while the TAs and MOs can be static or follow a random directional mobility. The U EDs are receiving and displaying a particular video content at a certain throughput (Th_u), expressed in bits per second (bps), according to the specific network conditions, the display and video resolutions.

Table I summarizes the considered video resolution and corresponding encoding bitrate for each kind of ED (MO/TA or PC/TV) according to [6]. Specifically, we consider up to 4K (3840×2160) video resolution for PC/TV. Regarding MO/TA, we evaluate from low-resolution videos (i.e., 480×270) to 2560×1440 resolution. Besides, we consider videos with three different codecs (H.264, H.265, and VP9), and we assume a fixed display resolution for MO/TA (2560×1440) and PC/TV (3840×2160) and a fixed frame rate of up to 60 fps.

Effective service delivery leverages radio resource management (RRM) by executing the fast link adaptation for selecting the appropriate modulation coding scheme (MCS) and required RBs. The transmitters carry out such selection every transmission time interval (TTI) $t^{'}$ after the U EDs report their feedback channel quality information (CQI_u), as detailed in [10]. The reported CQI_u is directly related to the signal-to-interference-noise-ratio ($SINR_u$), expressed in dBm, experienced by the ED_u.

We denote as eff_u the efficiency value (in bps/Hz) associated with the selected MCS of each ED_u. Then, the Th_u that can receive the ED_u is computed as

$$Th_u = n_u \times W_0 \times eff_u, \tag{1}$$

where n_u is the number of RBs assigned to the ED_u for proper reception of the video service encoded in a specific resolution. n_u is less than or equal to the number of available RBs (n_b^{av}) to attend to the ED_u in the BS_b.

Ec_u, expressed in joules (J), is the energy consumption by the user accessing the video service via the BS_b

$$Ec_u = P * D_u, \tag{2}$$

where P, expressed in watts (W), is the power consumed by the ED_u for the specific video reception. D_u, expressed in seconds, is the transmission delay experienced by the ED_u to access the video service through the BS_b [11].

Finally, the QoE perceived by the ED_u is expressed by QoE_u in terms of the traditional five-point Absolute Category Rating (ACR) scale of the Mean Opinion Score (MOS) [12].

TABLE I: The considered video resolutions [6].

Video resolution (MO/TA)	Bitrate (Mbps)	Video resolution (PC/TV)	Bitrate (Mbps)
480 × 270	[0.09,1)	720 × 540	[0.15,4)
720 × 540	[1,4)	1280 × 720	[4,10)
1280 × 720	[4,10)	1920 × 1080	[10,15)
1920 × 1080	[10,15)	2560 × 1440	[15,20)
2560 × 1440	[15,20]	3840 × 2160	[20,45]

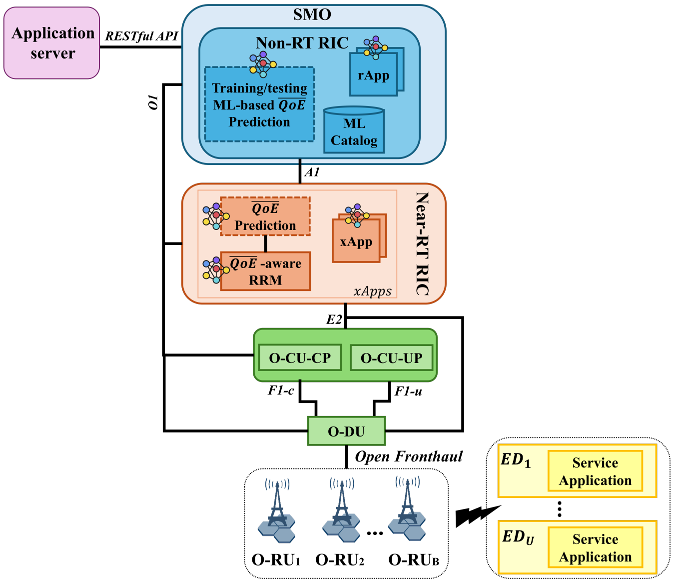

Fig. 1: The ML-based $\overline{QoE}$ prediction model inserted into the O-RAN framework. Service Management and Orchestration (SMO), Control Plane (CP), User Plane (UP), and Radio Unit (O-RU).

This value represents the per-second video quality estimation, whereas the overall QoE along the video session is defined by

$$\overline{QoE}_u = \frac{\sum_{t'=1}^{T'} QoE_u^{t'}}{T'}, \tag{3}$$

where T' is the number of samples with a resolution of 1 s.

B. The O-RAN Framework

We aim to obtain a reliable ML model to estimate the $\overline{QoE}$ of each ED_u only based on network and mobility information. This ML model must capture the variations of the EDs' position, their reception conditions, and the network load during the video session.

We propose inserting the ML-based $\overline{QoE}$ model into the O-RAN architecture, taking advantage of its disaggregated elements and open interfaces (Fig. 1). The O-RAN architecture facilitates $\overline{QoE}$ prediction and real-time optimization with a proactive closed-loop network control system. We assume MNO and SP collaboration to obtain a reliable ML-based $\overline{QoE}$ prediction model. Then, RAN, device, and application information are available during ML training.

For our proposal, we assume that the ML model ("Training/testing ML-based $\overline{QoE}$ Prediction") is trained offline in the Non-Real Time RAN Intelligent Controller (Non-RT RIC). The ML model inference ("$\overline{QoE}$ Prediction") is executed at the network edge in the Near-RT RIC, with control loops between 10 ms and 1 s [8]. As a first step, the Non-RT RIC gathers network data and devices' mobility behavior from the Open-RAN Central Unit (O-CU) and Distributed Unit (O-DU) through the *O1* interface. Simultaneously, it obtains the average QoE ($\overline{QoE}$) from the application server via *RESTful APIs* established between the MNO and SP. The collected data is preprocessed (e.g., cleaned and partitioned) and used to train various supervised ML regression models to estimate the $\overline{QoE}$ on a continuous MOS scale during the video sessions. Once the ML models are trained and evaluated, the model demonstrating the best performance is deployed to the Near-RT RIC through the *O1* interface. Additionally, the Non-RT RIC stores the trained ML model in the ML Catalog and deploys the QoE policy model for further operational use.

The Near-RT RIC stores the received ML-based $\overline{QoE}$ prediction model in the ML inference entity as an xApp to estimate the $\overline{QoE}$ only based on mobility and network-related information (obtained via the *E2* interface). The $\overline{QoE}$ prediction during the video-session execution allows for dynamic RRM (i.e., $\overline{QoE}$-aware RRM) or a handover process to improve user experience, embodying a human-centric network management. Additionally, the Non-RT RIC realizes long-term monitoring via the *O1* interface and sends *A1* policies and enrichment information to the Near-RT RIC. Specifically, the Non-RT RIC assesses the performance of the $\overline{QoE}$ ML model, retrains it if necessary, and updates it in the Near-RT RIC.

III. METHODOLOGY FOR DATA COLLECTION AND PREPARATION

This section presents the following methodology for data collection and preparation to properly define an ML-based $\overline{QoE}$ prediction model. The goal is to estimate the $\overline{QoE}$ on the continuous MOS scale for each ED_u during a video session using only the network and mobility information available at the MNO. First, we describe the data collection, including the ground truth $\overline{QoE}$. Then, we explain the data preparation. Fig. 2 illustrates the ML workflow, detailing the different steps from data collection to model deployment.

A. Data Collection

As mentioned in the previous section, we assume that MNO and SP collaborate to obtain a dataset with enough samples for ML training and testing. Our practical study obtains the data through link-level simulations on a per-second scale

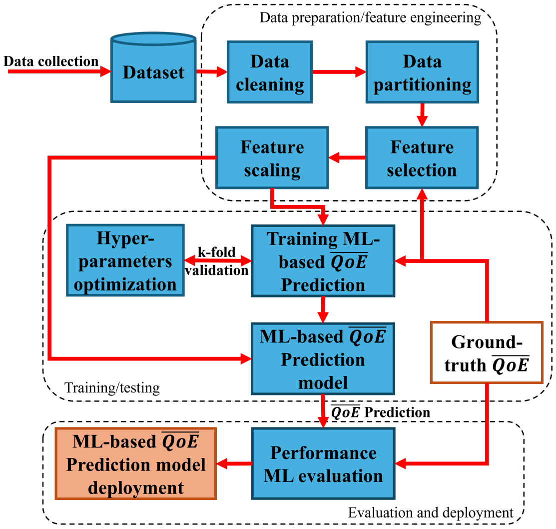

Fig. 2: Detailed ML workflow from data collection to model deployment.

TABLE II: Simulation parameters.

Parameter	Value
Scenario type	UMi Street Canyon [14]
Grid size	250×250 m
BS operating frequency	28 GHz [14]
NR numerology, μ	3
Bandwidth W / W_0	400 / 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
Height BS	10 m
Small/large-scale fading models	Jakes/ [13]
Type of EDs	MO, TA, PC, TV
Mobility MO, TA / PC, TV	Static, random directional/ static [13]
MO/TA speed	0-2 m/s
Reception MO, TA, PC / TV	Indoor-outdoor/Indoor

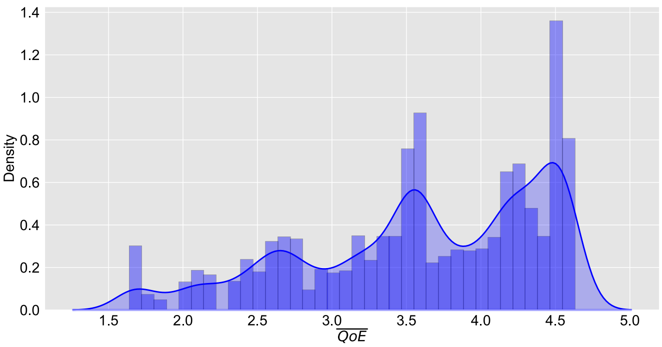

Fig. 3: Density distribution of the resulting $\overline{QoE}$ for the overall dataset.

TABLE III: Feature ranking using PCC and MI.

Ranking	PCC	MI
1	Th_u	$\overline{SINR_u}$
2	$\overline{SINR_u}$	Th_u
3	Ec_u	Ec_u
4	CQI_u	n_b^{av}
5	$SINR_u$	$SINR_u$
6	n_b^{av}	n_u
7	n_u	CQI_u
8	ν_u	$SINR_u^{std}$
9	$SINR_u^{std}$	ν_u

granularity, obtaining the $\overline{QoE_u}$ along the simulation for each ED_u. We use our ad-hoc developed Python-based tool [13] to model the link communication between the BS and the EDs, according to [13], [14]. To recreate diverse reception conditions, we simulate one NR micro BS in the center of a 250×250 m grid including 200 EDs ($U = 200$) randomly distributed. Regarding EDs, 50% are MOs or TAs, and the other 50% are TVs or PCs. We registered 50 seconds of simulation with a resolution of 1 second for a total of 10000 samples. Simulation parameters are specified in Table II.

Each collected sample corresponds to an ED_u including nine features, representing the information available at the MNO: the $SINR_u$ CQI_u, n_b^{av}, n_u, Ec_u, Th_u, and ν_u at time step t, and the mean and the standard deviation of the $SINR$ ($\overline{SINR_u}$, $SINR_u^{std}$). Specifically, the $\overline{SINR_u}$ and $SINR_u^{std}$ capture the SINR variation of ED_u over the simulation time ($t = 0, \ldots, t-2, t-1, t$). On the other hand, the $\overline{QoE_u}$ is the label of the ML model, supplied by the SP.

The ML target is to predict the $\overline{QoE}$ for each ED based on the one-per-second QoE as we defined in the equation 3. To obtain the one-per-second QoE, we consider the state-of-the-art QoE objective model described in the ITU-T Recommendation P.1204.3 concerning the video quality assessment of streaming services up to 4K resolution [12]. The model takes the video codec, frame rate, video encoding resolution, and display resolution as input. Then, it returns the QoE value on the five-point MOS scale, representing the per-second video quality estimation.

In particular, we have used the mode 0 bitstream model, which settles on the degradation-based modeling principle: the higher the degradation, the lower the video quality. This model considers three different degradations: quantization, upscaling, and frame rate [15], [16]. In the case of the quantization degradation, it slightly modifies the equation presented in [12] by lacking full bitstream information.

Fig. 3 shows the density distribution of the $\overline{QoE}$ for the overall collected dataset. We iteratively tune the simulation setup to obtain a representative distribution of EDs poor $\overline{QoE}$ ($\overline{QoE}$< 3), average ($3 \leq \overline{QoE}$< 4) and good $\overline{QoE}$ value ($\overline{QoE} \geq 4$) during the simulated video session.

B. Data Preparation

This subsection describes the procedures followed to pre-process the collected MNO features. We did not apply data cleaning during the data preparation because there were no missing values or outliers. The data was randomly partitioned into 80% and 20% for training and testing, ensuring each new subset is a representative part of the entire dataset to avoid a possible bias. Then, we applied feature selection using only the

TABLE IV: ML training/testing results.

Metric / ML model	LASSO	LR	SVR	MLP	RF	kNN	GB
R^2 (training)	0.854	0.856	0.965	0.981	0.986	0.990	0.991
R^2 (testing)	0.850	0.852	0.961	0.977	0.983	0.985	0.986
MAE (testing)	0.245	0.244	0.010	0.077	0.071	0.056	0.054
$MedAE$ (testing)	0.221	0.224	0.077	0.005	0.051	0.035	0.034
$MAPE(\%)$ (testing)	7.35	7.28	3.03	2.49	2.13	1.18	1.16
MSE (testing)	0.091	0.090	0.023	0.014	0.011	0.009	0.008
$RMSE$ (testing)	0.302	0.300	0.152	0.118	0.106	0.094	0.091
PCC (testing)	0.922	0.923	0.981	0.989	0.991	0.992	0.993

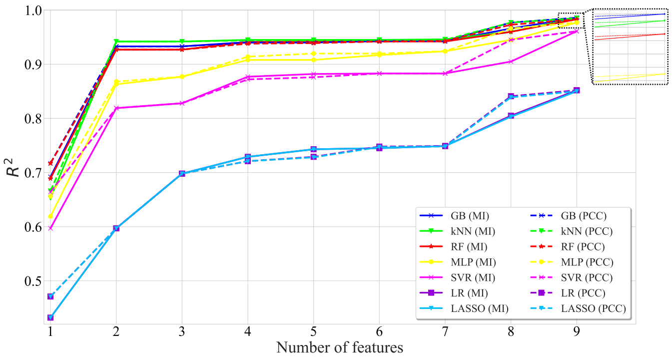

Fig. 4: R^2 results for an incremental number of features (ML testing).

training data to capture the relationship between the features and the $\overline{QoE}$ label.

Table III summarizes the feature ranking using the Pearson correlation coefficient (PCC) and Mutual Information (MI). The former captures the linear relationship among variables, where $+1$ represents a positive correlation, zero means variables are not correlated, and -1 denotes a negative correlation [17]. The latter captures linear and non-linear relationships between variables, where a high score means a high correlation [18], [19]. With both methods, $\overline{SINR}$, Th and Ec are the most correlated features, whereas ν and $SINR_{std}$ are the least representative. Finally, the feature scaling module used $MinMaxScaler$ to normalize the input data, leading to more stable and efficient training [18]. As we proved diverse supervised ML regression models, this step was applied to all models except Random Forest (RF) and Gradient Boosting (GB), which are less sensitive to different scales.

IV. EXPERIMENTAL RESULTS

A. ML Models Training/Testing

We trained seven ML regression models to estimate the $\overline{QoE}$ on the continuous MOS scale for video services based only on the network information and the users' mobility behavior. The following ML models were selected based on the state-of-the-art, which proved their applicability for wireless communications applications: Least Absolute Shrinkage and Selection Operator (LASSO), Linear Regression (LR), Support Vector Regression (SVR), k-Nearest Neighbors (kNN), MLP, RF, and GB. Each ML model has different hyperparameters that significantly influence the algorithm's performance. Then, we applied Grid-search and k-fold cross-validation (k=5) to explore the hyperparameter space and fine-tune it (Fig. 2). This step helps avoid overfitting and ensures a robust model's performance for unseen data [20].

To evaluate the performance of the ML models, we utilized the coefficient of determination (R^2), mean absolute error (MAE), median absolute error ($MedAE$), mean absolute percentage error ($MAPE$), mean squared error (MSE), root mean squared error ($RMSE$), and PCC. While R^2 and $RMSE$ are typically the preferred metrics for regression tasks [18], [21], we also included the other metrics to provide a more comprehensive assessment of model performance.

B. ML Models performance

According to the feature ranking obtained with PCC and MI, we proved the ML models from 1 to 9 features in an iterative process. Fig. 4 shows the outcomes in terms of R^2 for an incremental number of features following the ranking. As we can observe, the ML models accomplished the best results using all considered inputs (i.e., 9 features).

Table IV shows the ML training results in terms of R^2 using all features. Moreover, it details the ML testing results in terms of R^2, MAE, $MedAE$, $MAPE$, MSE, $RMSE$, and PCC. During the ML testing, GB achieved the best performance with an $R^2 = 0.986$ and $RMSE = 0.091$. Moreover, GB exhibited a very strong positive correlation between the predicted $\overline{QoE}$ and the ground truth ($PCC = 0.993$). These results were obtained with the following hyperparameters: $learning\_rate = 0.08$, $max\_depth = 6$, $min\_samples\_leaf = 5$, $min\_samples\_split = 2$, $n\_estimators = 100$, $subsample = 0.5$, and $n\_jobs = -1$. For completeness, although slightly lower than GB, the kNN, RF, MLP, and SVR models have also achieved good $\overline{QoE}$ prediction results.

Additionally, Fig. 5 shows the residuals of estimating the $\overline{QoE}$, detailing under-estimations and over-estimations. We did not include LASSO in Fig. 5 because this ML model presented almost the same performance as LR, as shown in Fig. 4. The ML models present less dispersion for $\overline{QoE} \geq 4$ because the dataset has more samples with these characteristics, as shown in Fig. 3. Then, to reduce the dispersion of estimating lower $\overline{QoE}$ values, it is necessary to have a higher dataset with a more balanced sample distribution in the MOS range.

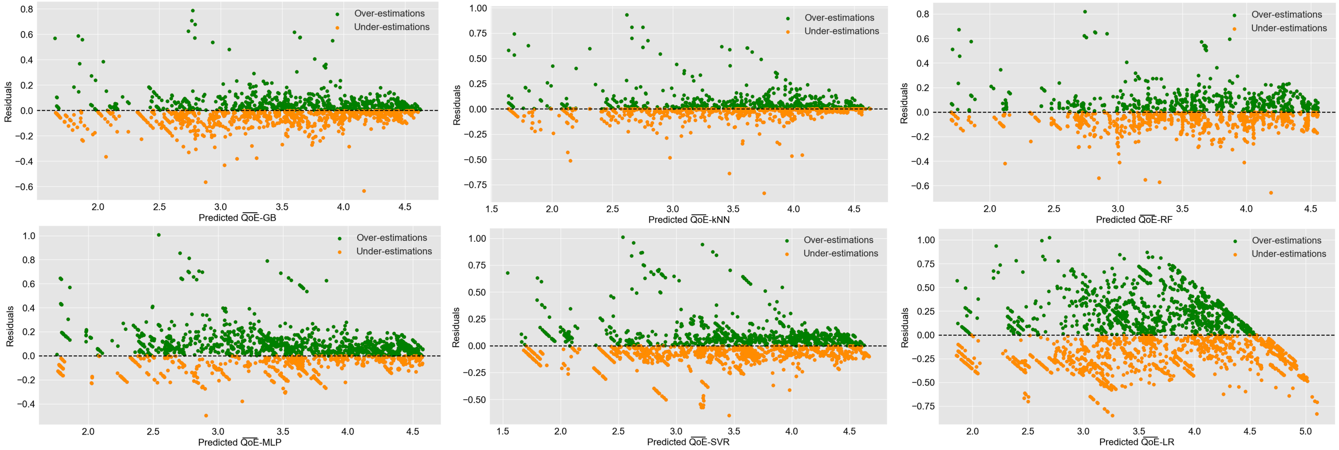

Fig. 5: Deviation on the $\overline{QoE}$ estimation based on network and mobility information.

V. CONCLUSIONS

This paper presents an ML-based model inserted into the 5G O-RAN architecture for predicting QoE variations of multiple EDs during a video session. The proposal is a unified tool designed to address fixed and mobile devices playing videos encoded with different codecs up to 4K resolution and 60 fps over the 5G network infrastructure. By fostering collaboration between OTT platforms and MNOs, the approach leverages data sharing and advanced ML techniques to achieve accurate QoE predictions. Moreover, the ML inputs rely solely on network and mobility data, addressing MNOs' lack of access to application-level data. The ML model can capture the QoE variations during a video session, influenced by the EDs' mobility behavior, the channel quality conditions, and available network resources. Performance evaluation showed that Gradient Boosting excelled compared with the other six supervised regression ML models, with $R^2 = 0.986$ and $RMSE = 0.091$ during the testing process.

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