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# A QoE-based Energy-aware Resource Allocation Solution for 5G Heterogeneous Networks

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**Abstract**—The increasing demand for quality from multimedia service users is very often addressed by adding more resources (bandwidth and processing power). However, not always does this approach bring an improvement in the perceived quality, whereas it frequently implies an increase in energy consumption (and subsequent higher greenhouse gas emissions). Accordingly, in this paper, we propose a solution to dynamically allocate resources in a 5G heterogeneous network scenario, which aims to identify a trade-off between the overall QoE perceived by the users served by the network when consuming video content and the overall network energy consumption. We considered three types of devices (TV, laptop, and smartphone) for which appropriate QoE and energy consumption models are defined. Extensive simulations have been performed by assigning different levels of importance to QoE and energy. The achieved results show that the network energy consumption can be more than halved by keeping satisfactory QoE. This is particularly true for smartphone users, whereas TV and laptop users have the freedom to choose based on their sensitivity towards sustainability.

**Index Terms**—Quality of Experience, 5G Network, Video Streaming, Sustainability, Energy Consumption.

## I. INTRODUCTION

The rapid advancement of technology has led to an exponential increase in video streaming performance, significantly enhancing the user Quality of Experience (QoE). However, this progress has come at a cost: higher energy consumption. Indeed, while the delivery of video content at the highest quality undoubtedly contributes to providing satisfactory QoE, it also leads the end-to-end video delivery chain to massive energy usage, posing a substantial challenge to the goal of sustainable development adopted by all United Nations Member States, which is aimed to minimize greenhouse gas (GHG) emissions by 2030<sup>1</sup>.

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<sup>1</sup><https://sdgs.un.org/2030agenda>

The contribution of ICT is estimated at ca. 1.8%–2.8% of global GHG emissions in 2020 [1]. All studies include data centres, networks, and user devices as the three main components contributing to ICT’s carbon footprint. In particular, the network contribution is estimated at between 22 and 35%, depending on the estimation study. The evolution of mobile networks contributes to the goal of achieving energy-efficient networks. For example, the 5G New Radio (NR) standard has been designed to support sleep states in radio network equipment, which forces the base station to switch off some hardware components when there is no traffic to serve. This approach, coupled with the fact that 5G NR requires fewer transmissions of always-on signalling transmissions, allows for longer sleep periods when modest ongoing data transmission is involved, significantly reducing the overall network energy consumption [2]. However, a comprehensive understanding of the energy consumption of mobile networks is far to be complete. For instance, in [3], it is observed that the carbon emissions of the 5G network are lower, about 50% of those of the 4G network in terms of information transmission bit. On the contrary, in [4], it is reported that since the 5G bandwidth is still underutilized in short burst flows, it consumes  $1.67\times$  more energy than 4G when the end-device is running the same Web loading sessions.

But regardless of the transmission network, the study in [5] provides interesting insights concerning the relevance of data traffic and the device’s display size on the overall energy consumption of video streaming services. In particular, the higher the data traffic, the higher the energy consumption, and the smaller the device is (in terms of device size and screen resolution), the lower the energy consumption. Thus, a network management approach aimed at providing the greatest QoE to the served end users may lead to excessive energy consumption because the resources would be allocated to provide the highest quality content (highest resolution meaning larger data traffic) to the users. Indeed, this is the main limitation of most of the literature studies focused on network management, which implement QoE-centric resource allocation algorithms with no regard to sustainability [6]–[8].

However, recent studies have shown that some users (identified as *green users*) have become more attentive to the sustainability of ICT services and may opt to make a slight

sacrifice in QoE (keeping it to an acceptable level) to decrease carbon emissions [9], [10]. This is possible because it has been demonstrated, in particular for video streaming services, that higher service performance does not necessarily imply (significantly) greater perceived QoE [11], [12]. Thus, energy consumption can be diminished by providing a satisfactory level of QoE to the user rather than the maximum QoE. In particular, the results of the subjective assessment conducted in [13] showed that streaming lower-quality video would not necessarily lead to a noticeable QoE decrease (in particular, switching from the device's native resolution to the first lower resolution), whereas it would save a relevant amount of energy and network resources.

Based on these findings, in this paper, we present a solution to dynamically allocate resources in a 5G heterogeneous network (HetNet) scenario. The proposed solution aims to identify a trade-off between the overall QoE perceived by the users served by the network when consuming video content and the overall network energy consumption. We considered three types of devices (TV, laptop, and smartphone) and we defined a utility function taking into account the combined impact of QoE and energy consumption. We conducted extensive simulations by assigning different levels of relevance to QoE and energy and by considering two scenarios: serving all devices of the same type; and serving a combination of different device types. In the first case, smartphone users can always perceive the highest QoE by consuming the lowest energy; TV users can halve energy consumption with a negligible QoE reduction; and laptop users may decide to save about one-third of consumed energy by slightly sacrificing the QoE. In the second case, it is found that the overall energy consumption can be almost halved with no impact on the QoE.

The paper is structured as follows. Section II presents the proposed system model, whereas Section III details our proposed solution. In Section IV, we discuss the link-level simulations and the achieved results. Finally, Section V concludes the paper.

## II. SYSTEM OVERVIEW

Fig. 1 illustrates the proposed system model, which is considered to evaluate the energy consumption and QoE when streaming video content to the end devices through a 5G access network by varying the network setting. We assume a HetNet deployment, including a set of  $B$  NR base stations (BSs) defined by  $\mathbb{B}$ , with the sub-index  $b \in \{1, 2, \dots, B\}$ . Moreover, we consider a set of  $A$  NR access points (APs) defined by  $\mathbb{A}$ , with the sub-index  $a \in \{1, 2, \dots, A\}$ .

We assume a channel bandwidth  $W$  for the considered BSs and APs over an operating frequency  $f$  and embracing  $N$  physical resource blocks (RBs). An RB is the smallest frequency resource the BSs and APs can allocate, corresponding to 12 consecutive and equally spaced subcarriers, for an RB bandwidth  $W_n = 12 \times \Delta f$ . As defined by the 5G NR standard, we assume a numerology ( $\mu$ ) for the subcarrier spacing value defined as  $\Delta f = 15 \times 2^\mu$ , expressed in kHz [14].

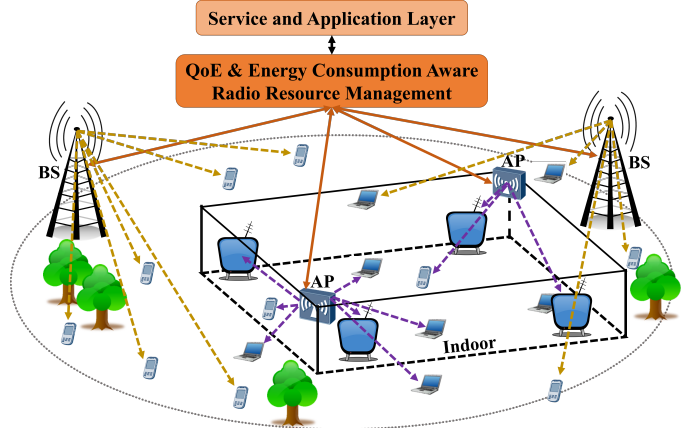


Fig. 1: The considered HetNet deployment scenario.

We assume that the network serves a set of  $D$  end-devices, randomly distributed in the considered area, denoted by  $\mathbb{D}$  with the sub-index  $d \in \{1, 2, \dots, D\}$ . We consider three types of end devices: TV, laptop (LP), and smartphone (SP) with  $i \in \{TV, LP, SP\}$ . The TVs and LPs are static and are connected to the APs. The SPs are characterized by random directional mobility and can be dynamically connected to either the BSs or the APs. The  $D$  end devices will be receiving and displaying a particular video content with a specific spatial resolution that will be characterized by a bitrate ( $BR_{i,d}$ ).

To effectively deliver the requested service, the set of available RBs at the BSs and APs are managed by executing the fast link adaptation procedures and selecting the most appropriate modulation coding scheme (MCS). The transmitters carry out such selection every transmission time interval (TTI)  $t$ , collecting from the  $D$  devices their experienced channel quality information ( $CQI_{i,d}$ ), as detailed in [15].

We denote, as  $eff_{i,d}$ , the efficiency value (in bits/s/Hz) associated with the channel reception conditions (s.t.  $CQI_{i,d}$ ) of each device  $d$  [15]. Then, the  $BR_{i,d}$  assigned to the device, expressed in bit/s, is computed as

$$BR_{i,d} = n_{i,d} \times W_n \times eff_{i,d}, \quad (1)$$

where  $n_{i,d}$  is the number of RBs assigned to  $d$  for proper reception of the video content encoded at a specific resolution.

Concerning the estimation of the QoE and energy consumption for each device  $d$ , we based on the study in [13], where a subjective assessment is conducted to investigate the impact of different luminance configurations and video resolutions on the QoE and energy consumption in video streaming on various device types. We predict the QoE perceived by the user of a device  $d$  in terms of the Mean Opinion Score (MOS) as a function of the reproduced video  $BR_{i,d}$  and the level of backlight luminance ( $BL_{i,d}$ ) set on the device. The predicted MOS is defined as  $MOS_{i,d}^p = f(BR_{i,d}, BL_{i,d})$ . The details of the QoE model definition for the three considered devices are described in Section III-A.

We quantify the end-to-end (from the data centre to end device) energy consumed to stream the video on a device  $d$

in terms of the overall electricity consumption,  $Q_{i,d}$  (kWh), estimated using the following equation [5]:

$$Q_{i,d} = t_{i,d} \times (P_{i,d} + R_{i,d} \times \rho), \quad (2)$$

where  $t_{i,d}$  is the streaming hour over a week,  $P_{i,d}$  is the device's power load depending on the BR of the reproduced video and, mainly, on the device's level of BL,  $R_{i,d}$  is the transmitted data traffic proportional to the BR of the reproduced video, and  $\rho$  is a factor accounting for the electricity intensity of data traffic, including data transmission network and data centre. For video encoded at HD, FHD, and 4K spatial resolution,  $R$  assumes values around 1, 2, and 9 GB/h. The power load  $P$  ranges from a few or dozens of W for SP and LP, respectively, whereas more than 200 W are needed by a 4K TV set with the brightest BL level. Setting the TV to the darkest BL level saves up to one-quarter of the consumed power. Note that the values of  $t$ ,  $P$ ,  $R$ , and  $\rho$  for the three types of devices can be found in [13].

The provided level of QoE and energy consumption depends on both the BR of the video reproduced on the device and the level of BL of the device. However, while the video BR can be controlled on the network management side, the level of BL is decided by the user. We propose to optimize the BR assigned to the devices connected to the network according to a utility function that combines the contribution of QoE and energy and allows us to provide different weights to these two factors. The proposed approach relies on centralized management, as depicted in Fig. 1, where the resource management module retrieves the CQI of each device and, based on the importance given to QoE and energy consumption driven by the utility function, decides the video BR to be reproduced on that device.

### III. PROPOSED SOLUTION

In this section, we initially present the defined QoE models (Section III-A), and then we present the proposed resource allocation algorithm (Section III-B).

#### A. QoE Modelling

This section introduces three QoE models designed explicitly for the three considered end devices: TV (60" UHD 4K screen,  $3840 \times 2160$  pixels), LP (15.6" FHD screen,  $1920 \times 1080$  pixels), and SP (5.5" FHD screen,  $1920 \times 1080$  pixels). Each QoE model is defined from the dataset of the subjective scores collected from the assessment conducted in [13], whose results highlighted the combined contribution of the device's level of BL and the BR of the reproduced video on both the QoE and the electricity consumption of the video streaming delivery chain. Thus, by considering changes in BL and BR, we can measure QoE and energy consumption changes.

We defined the QoE models by considering BR and BL as the dependent variables and the MOS as the variable to be predicted. The values of BR and BL for each of the three device types can be found in [13]. Note that we are not considering ambient luminance and content luminance, which were two further variables included in the test conditions of

the subjective assessment, because their effect on QoE and energy consumption were found to be negligible; moreover, they cannot be controlled because they intrinsically depend on the ambient conditions and video content, respectively.

We applied a Linear Regression model to model the relationship between BR, BL, and the MOS for each end device. We performed 5-fold cross-validation to achieve more accurate results. The defined QoE models, which return the predicted MOS for the TV, LP, and SP device types, are represented by the equations (3), (4) and (5), respectively.

$$MOS_{TV}^p = 0.030 \times BR_{TV} + 0.708 \times BL_{TV} + 3.426 \quad (3)$$

$$MOS_{LP}^p = 0.606 \times BR_{LP} + 0.506 \times BL_{LP} + 2.797 \quad (4)$$

$$MOS_{SP}^p = -0.025 \times BR_{SP} + 1.975 \times BL_{SP} + 1.950 \quad (5)$$

The coefficients in the linear regression models represent the weights or importance of the corresponding variables BR and BL in predicting the MOS for each device type. The impact of the BL on the QoE of the SP's users is the most important, suggesting that the darkest level of BL would significantly decrease the QoE. However, the BL has a relevant impact also on the QoE perceived by users of TV and LP. Concerning the BR of the reproduced video, this has a significant impact only on the QoE of LP's users, whereas it is negligible for TV and SP. The negative coefficient for the BR of SP is because users were not able to distinguish between the two reproduced video qualities (FHD and HD) on the small SP's screen, and provided slightly higher scores when they watched HD videos.

The model's performance was evaluated in terms of the Root Mean Square Error (RMSE) and the Pearson Correlation Coefficient (PCC). The RMSE values were obtained as 0.26, 0.21, and 0.12 for  $MOS_{TV}^p$ ,  $MOS_{LP}^p$  and  $MOS_{SP}^p$ , respectively. The PCC values were obtained as 0.80, 0.87, and 0.99 for  $MOS_{TV}^p$ ,  $MOS_{LP}^p$  and  $MOS_{SP}^p$ , respectively. Note that these are the average RMSE and PCC values over the 5 folds.

#### B. QoE and Q based Resource Allocation Algorithm

Once the QoE models for each device type  $i$  are obtained, we have implemented a heuristic solution to optimize resource allocation in a 5G heterogeneous environment. To make the decision, we have defined a dimensionless utility function ( $UF_{i,d}$ ) that combines the  $Q_{i,d}$  and  $MOS_{i,d}^p$  metrics for each device  $d$ . It is defined as:

$$UF_{i,d} = \alpha \times Q_{i,d}^N + (1 - \alpha) \times MOS_{i,d}^{p,N}, \quad (6)$$

where  $\alpha$  adjusts the importance given to the electricity consumption and user's QoE. The  $Q_{i,d}$  and  $MOS_{i,d}^p$  metrics have different units of magnitude that make a fair comparison impossible [16]. Therefore, we normalized them to ensure their proportional contribution to the  $UF_{i,d}$ , adjusting its value between 0 and 1 ( $UF_{i,d} \in [0, 1]$ ).

The normalized MOS ( $MOS_{i,d}^{p,N}$ ) is calculated using the utility function upward criterion's equation [17]:

$$MOS_{i,d}^{p,N} = \begin{cases} 0, & \text{s.t. } Cond_1 \\ 1 - \frac{MOS_i^{max} - MOS_{i,d}^p}{\delta' \times (MOS_i^{max} - MOS_i^{min})}, & \text{s.t. } Cond_2 \\ 1, & \text{otherwise.} \end{cases} \quad (7)$$

$$Cond_1: MOS_{i,d}^p < MOS_i^{min},$$

$$Cond_2: MOS_i^{min} \leq MOS_{i,d}^p \leq MOS_i^{max}.$$

$MOS_i^{min}$  and  $MOS_i^{max}$  are the minimum and maximum MOS values according to the device type  $i$ , the reproduced video bitrate  $BR_{i,d}$ , and the device's level of backlight luminance  $BL_{i,d}$ . Additionally,  $\delta' \geq 2$  is a tuned steepness parameter [16].

On the contrary, to obtain the normalized  $Q_{i,d}$  ( $Q_{i,d}^N$ ), we use the utility function downward criterion's equation [17]:

$$Q_{i,d}^N = \begin{cases} 1, & \text{if } Q_{i,d} < Q_i^{min} \\ 1 - \frac{Q_{i,d} - Q_i^{min}}{\delta' \times (Q_i^{max} - Q_i^{min})}, & \text{if } Q_i^{min} \leq Q_{i,d} \leq Q_i^{max} \\ 0, & \text{otherwise,} \end{cases} \quad (8)$$

where  $Q_i^{min}$  and  $Q_i^{max}$  are the minimum and maximum  $Q_i$  tolerated values according to each device type  $i$ ,  $BR_{i,d}$ , and  $BL_{i,d}$ .  $Q_i^{min}$  and  $Q_i^{max}$  are computed using eq. (2).

At each TTI  $t'$ , the system detects if there are new devices in the network. Then, it is executed an iterative process to associate such new devices with the BS or AP that guarantees the maximum  $UF_{i,d}^{t'}$  ( $UF_{i,d}^{max,t'}$ ). Moreover, at each  $t'$ , if the system detects a variation in the reception conditions (i.e.,  $CQI_{i,d}^{t'}$  feedback) of a current device  $d$  in the network, the algorithm is re-executed. As a consequence, to maximize the  $UF_{i,d}^{t'}$ , the device could be changed to a new access network (i.e., the handover process), or it could be updated the MCS and corresponding  $n_{i,d}^{t'}$  in the current access network. The network selection and handover processes rely on more than a resource availability perspective. We consider the network and user sides, combining the QoE and energy consumption metrics as the decision criteria factors.

The algorithm can be formulated as a long-term utility optimization problem to maximize the  $UF_{i,d}$ ,  $\forall d \in \mathbb{D}$

$$\max \sum_{t'} \sum_d UF_{i,d}^{t'} \quad (9a)$$

$$\text{s.t. } BR_{i,d}^{t'} \geq BR_i^{min}, \quad (9b)$$

where  $BR_i^{min}$  is the lowest bitrate reproduced on the device type  $i$ .

#### IV. PERFORMANCE EVALUATION

This section presents our proposal assessment and analysis through simulation results of a recreated 5G heterogeneous environment when delivering a video service to multiple types of end devices. The simulations were carried out using an ad-hoc 5G link-level simulator (LLS) [18] developed in Python. The first subsection details the simulation settings and

TABLE I: Simulation parameters.

Parameter	Value
Number of BS/AP	1/2
BS/AP Operating frequency	28 GHz [14], [19]
BS/AP Bandwidth, $W$	400 MHz
NR numerology, $\mu$	3
RB's bandwidth, $W_n$	1.44 MHz
Subcarrier spacing	120 kHz
Transmission power AP/BS	40 dBm/26 dBm
Power Spectral density of noise	-174 dBm/Hz
Height BS/AP	10 m/4 m
Small/Large-scale fading models	[18]
Dynamic line of sight	Yes
Number of end devices	100
Type of end devices	TV, LP, SP
Height of end devices	1.5 m
Mobility Model TV/LP/SP	Static/Static/Random directional [18]
Reception mode TV/LP/SP	Indoor/Indoor-Outdoor/Indoor-Outdoor
SP' speed	0-0.8 m/s
Service type	Video
Video resolution TV/LP/SP	4K-FHD/FHD-HD/FHD-HD
Video bitrate (s.t., resolution) TV/LP/SP (Mbps)	20-5/5-2/5-2
Backlight luminance TV/LP/SP (lx)	5500-300/4000-400/5000-200

considerations. Then, we present the achieved results and the corresponding analysis.

##### A. Simulation Settings

We recreate a heterogeneous environment composed of one outdoor NR micro-BS ( $B = 1$ ) and two indoor NR APs ( $A = 2$ ). We consider an operating frequency  $f = 28$  GHz, with an NR numerology  $\mu = 3$  for an  $W_n$  equal to 1.44 MHz as detailed in [14], [19]. We define a maximum of 100 connected devices ( $D = 100$ ) receiving and displaying a particular video service. Table I summarizes the main simulation parameters. While we consider this specific setting, the proposed system can be successfully applied with other network configurations.

During our simulations, we evaluate two particular scenarios that are described as follows:

- Scenario A: The 100% of the devices are assumed as TVs, LPs, or SPs to analyze their independent behavior and impact regarding the  $UF$  considerations. Different BL configurations are evaluated.
- Scenario B: The 75% of the devices are assumed to be SPs, and the remainder 25% are randomly distributed between TVs and LPs. The BL is randomly assumed. This setting is oriented to assess the impact regarding the  $UF$  considerations of a heterogeneous distribution of end devices. In this case, the results were achieved by averaging 30 simulation runs to ensure a 95% confidence interval.

Note that  $BL = 0$  and  $BL = 1$  in Figs. 2, 3, and 4 are a simple notation to indicate the darkest and the brightest values of BL set on the respective device, whose actual BL values are reported in Table I.

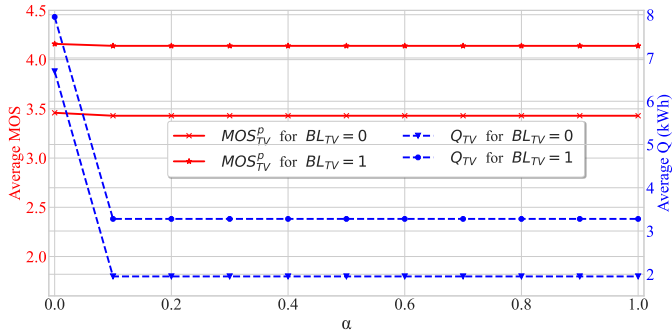


Fig. 2: Average  $MOS_{TV}^p$  and  $Q_{TV}$  for  $UF_{TV}^{max}$  and different  $\alpha$  values.

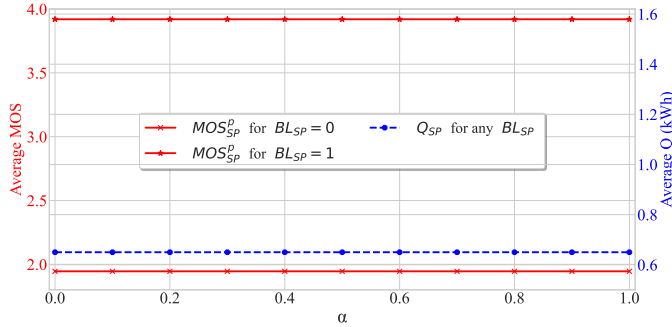


Fig. 3: Average  $MOS_{SP}^p$  and  $Q_{SP}$  for  $UF_{SP}^{max}$  and different  $\alpha$  values.

## B. Results and Analysis

1) *Scenario A Results:* Figs. 2, 3, and 4 show the trade-off between  $MOS_{i,d}^p$  and  $Q_{i,d}^p$  for different  $\alpha$  values. The results display the achieved  $MOS_{i,d}^p$  and  $Q_{i,d}^p$  average values that maximize the  $UF_{i,d}$  and consequently eq. (9) for TVs, SPs, and LPs separately.

Particularly, Fig. 2 illustrates the case where all devices are TVs. As we explained in Section III-A, the  $MOS_{TV,d}^p$  is basically determined by the BL because the BR has a minimal contribution (due to the weight coefficient value in eq. (3)). On the contrary, a variation in  $BR_{TV,d}$  directly impacts  $Q_{TV,d}$  because of the large difference in data traffic required by 4K videos compared to FHD videos. As Fig. 2 shows, only for  $\alpha = 0$  the MOS is prioritized, and the  $UF_{TV,d}^{max}$  is reached with  $BR_{TV,d}^{max}$ ,  $MOS_{TV,d}^{max}$  and  $Q_{TV,d}^{max}$ . Then, for any  $\alpha > 0$ , the  $UF_{TV,d}$  is optimized reducing the  $BR_{TV,d}$  and as consequence  $Q_{TV,d}$  and  $MOS_{TV,d}^p$  values. From the  $MOS_{TV,d}^p$  perspective, the reduction of the  $BR_{TV,d}$  from 4K to FHD involves an insignificant QoE reduction, whereas it saves network resources and significantly decreases electricity consumption (more than halved). Setting the TV's BL from the brightest to the darkest level slightly reduces the QoE (half point of MOS) and the electricity consumption.

Fig. 3 shows the result where all considered devices are SPs. In this case, the BR also has a very small contribution to the  $MOS_{SP,d}^p$ , but the weight coefficient is negative, as we explained in Section III-A. Then, even with  $\alpha = 0$ , the

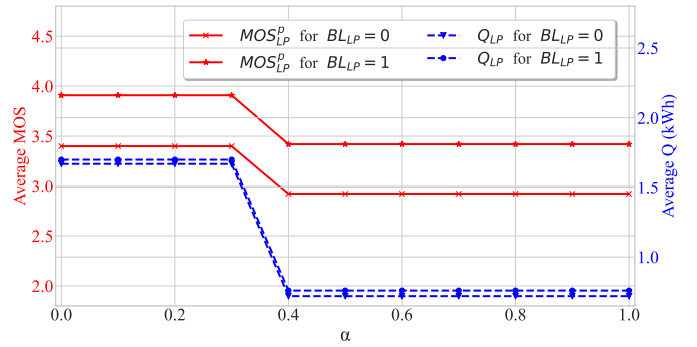


Fig. 4: Average  $MOS_{LP}^p$  and  $Q_{LP}$  for  $UF_{LP}^{max}$  and different  $\alpha$  values.

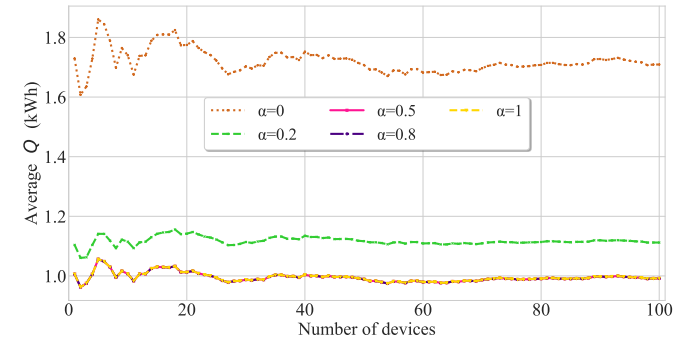


Fig. 5: Average  $Q$  for different numbers of devices in the network.

$UF_{SP,d}^{max}$  is obtained with  $Q_{SP,d}^{min}$ ,  $BR_{SP,d}^{min}$ , and  $MOS_{SP,d}^{max}$  for any  $BL_{SP,d}$  configuration. It means that according to the defined QoE model for SPs in the specific recreated conditions, the optimization process always assumes a green profile. Thus, there is no need for green users to set the SP's BL from the brightest to the darkest level because this would totally decrease the QoE (from good to poor) with no electricity reduction.

On the other hand, Fig. 4 evidences how the BR and BL have a comparable impact on the  $MOS_{LP,d}^p$ , as a consequence of the QoE model presented for LPs. Specifically, for  $\alpha < 0.4$ , the  $UF_{LP,d}^{max}$  is achieved with  $BR_{LP,d}^{max}$  and  $MOS_{LP,d}^{max}$  at the expense of increasing the electricity consumption ( $Q_{LP,d}^{max}$ ). However, green users can decide to make a sacrifice in QoE (half point of MOS) to save a significant amount of energy (reduced by one-third when  $\alpha \geq 0.4$ ). This QoE sacrifice due to the video quality reduction would be more tolerable when the LP's BL is set to the brightest level (MOS from 4 to 3.5) than to the darkest level (MOS from 3.5 to 3).

2) *Scenario B Results:* Fig. 5 shows the average  $Q_{i,d}$  for different numbers of devices in the network. As expected from the previous graphs, the algorithm employing  $\alpha = 0$  prioritizes the MOS, causing an increment in electricity consumption. However, Fig. 6 evidences that the increment in  $Q_{i,d}$  for  $\alpha = 0$  is not justified due to the difference in the average  $MOS_{i,d}^p$  regarding  $\alpha = 0.2$  being very small. Moreover, as

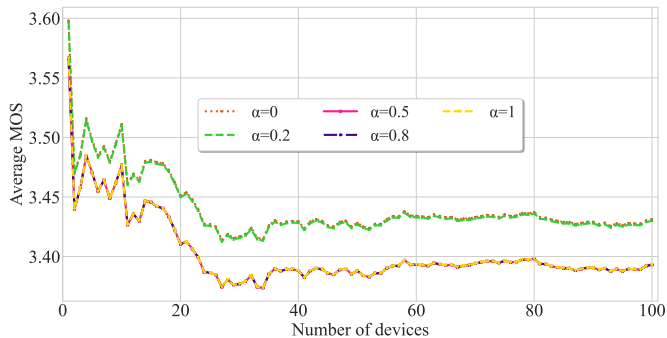


Fig. 6: Average  $MOS$  for different numbers of devices in the network.

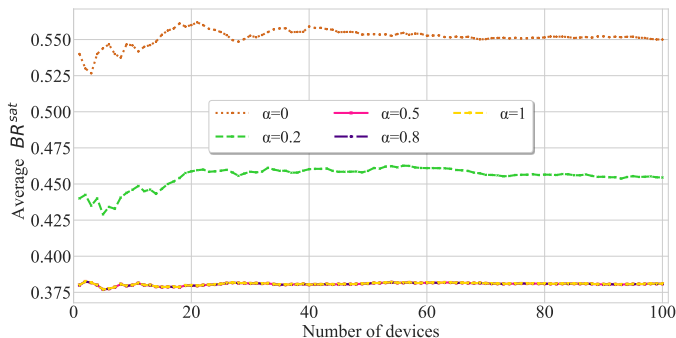


Fig. 7: Average  $BR^{sat}$  for different numbers of devices in the network.

we presented in Figs. 2, 3 and 4, for  $\alpha > 0$  in the case of SPs and TVs, and for  $\alpha \geq 0.4$  in the case of LP, the  $UF_{i,d}$  optimization is achieved minimizing  $Q_{i,d}$ . Then, the resulting average  $MOS_{i,d}^p$  values for the represented  $\alpha = \{0.5, 0.8, 1\}$  are less than the values observed for  $\alpha = \{0, 0.2\}$ . Again, this result demonstrates how the users could opt to slightly sacrifice their own QoE in order to save electricity consumption.

Finally, Fig. 7 shows the average BR satisfaction ( $BR_{i,d}^{sat}$ ) for different numbers of devices in the network. The  $BR_{i,d}^{sat}$  is the ratio between the assigned  $BR_{i,d}$  and the  $BR_{i,d}^{max}$  corresponding to the highest video resolution defined for  $i$ . Then,  $BR_{i,d}^{sat} = 1$  means that the network assigns to the device  $d$  the  $BR_{i,d}^{max}$ . For the recreated conditions, even with  $\alpha = 0$ , the average  $BR_{i,d}^{sat}$  is less than 0.57. If we analyzed this result alone, just taking into account the BR, it seems to be a drawback of the proposed algorithm. However, analyzing all the figures as a whole, we demonstrate that decreasing the overall  $BR_{i,d}$  reduces the  $BR_{i,d}^{sat}$ , but it does not considerably affect the perceived QoE while saving energy and radio resources. For example, for a TV with  $CQI_{TV,d} = 9$ , the number of required RBs to achieve the  $BR_{TV,d}^{max} = 20$  Mbps is  $n_{TV,d} = 4$ , whereas for  $BR_{TV,d}^{min} = 5$  Mbps is  $n_{TV,d} = 1$ .

As demonstrated, for any considered device and  $\alpha \geq 0.4$ , the  $UF_{i,d}$  is optimized, minimizing  $Q_{i,d}$  and reducing the number of needed RBs. These released resources could be used to serve new devices or enrich the QoE of impaired

ones. For example, for the specific recreated conditions with 100 devices in the network, using  $\alpha \geq 0.4$  reduces in 22% the number of RBs required concerning  $\alpha = 0$ . Moreover, the results demonstrated that a variation in the  $BR_{i,d}$  for SPs and TVs has a very small contribution to the  $MOS_{i,d}$ . Nevertheless, in the case of LPs, we must manage  $\alpha$  regarding the client's expectations and the sustainability profile we choose to follow. The proposed resource allocation process is an integral solution that ensures an adequate overall QoE being aware of the electricity consumption.

## V. CONCLUSION

We proposed a solution to dynamically allocate resources in a 5G HetNet scenario driven by the compromise between the overall energy consumed by the end-to-end network infrastructure and the end user's QoE. We based on the fact that the allocation of additional network resources does not always increase the perceived quality but it often consumes more energy. To validate the proposed solution, we set a simulation scenario involving a 5G access network aimed to serve 100 devices of different types (TV, laptop, and smartphone). We defined proper QoE and energy consumption models (as a function of the reproduced video bitrate and the device's level of backlight luminance) for each device type and we performed simulations by defining a utility function that assigns different levels of importance ( $\alpha$ ) to QoE and energy.

When all devices are assumed to be of the same type, we achieve different results depending on the device type. For TV devices, reducing the video BR implies a negligible decrease in the user's QoE but energy consumption is more than halved. For SP devices, the same energy level is consumed regardless of the BR and BL values. However, the darkest level of BL on the SP dramatically reduces the QoE, which allows SP users to be green even by setting the brightest BL. For LP devices, the choice to be green is left to the user because they can decide to make a sacrifice in QoE (half point of MOS) to reduce energy consumption by one-third.

When considering different device types together (75% SPs, 25% between TVs and LPs), we found that a huge reduction in energy consumption corresponds to a tiny decrease in QoE. Specifically, by setting  $\alpha = 0.2$  the energy consumption is almost halved with no noticeable QoE reduction, whereas with  $\alpha = 0.5$  the energy consumption is more than halved with slight QoE reduction (0.15 of MOS).

We acknowledge that the achieved results are in part driven by the considered subjective data and end device types. However, the proposed solution remains valid even with diverse and updated QoE and energy consumption models, which are currently missing in the literature. Indeed, future work must be focused on a deep exploration of the relationship between QoE and energy consumption, to better tune network management approaches towards the optimal trade-off between these two aspects, which aim to make ICT services more sustainable while keeping the users satisfied.

## REFERENCES

- works," *IEEE Transactions on Broadcasting*, vol. 67, no. 3, pp. 593–605, 2021.
- [1] C. Freitag, M. Berners-Lee, K. Widdicks, B. Knowles, G. S. Blair, and A. Friday, "The real climate and transformative impact of ICT: A critique of estimates, trends, and regulations," *Patterns*, vol. 2, no. 9, p. 100340, 2021.
  - [2] J. Pang, S. Wang, Z. Tang, Y. Qin, X. Tao, X. You, and J. Zhu, "A new 5G radio evolution towards 5G-Advanced," *Science China Information Sciences*, vol. 65, no. 9, p. 191301, 2022.
  - [3] Y. Ding, H. Duan, M. Xie, R. Mao, J. Wang, and W. Zhang, "Carbon emissions and mitigation potentials of 5G base station in China," *Resources, Conservation and Recycling*, vol. 182, p. 106339, 2022.
  - [4] D. Xu, A. Zhou, X. Zhang, G. Wang, X. Liu, C. An, Y. Shi, L. Liu, and H. Ma, "Understanding Operational 5G: A First Measurement Study on Its Coverage, Performance and Energy Consumption," in *Proc. of the Annual Conf. of the ACM Special Interest Group on Data Communication on the Applications, Technologies, Architectures, and Protocols for Computer Communication*, ser. SIGCOMM '20. ACM, 2020, p. 479–494.
  - [5] P. Suski, J. Pohl, and V. Frick, "All you can stream: Investigating the role of user behavior for greenhouse gas intensity of video streaming," *Proceedings of the 7th International Conference on ICT for Sustainability*, 2020.
  - [6] M. T. Sultan and H. El Sayed, "QoE-Aware Analysis and Management of Multimedia Services in 5G and Beyond Heterogeneous Networks," *IEEE Access*, vol. 11, pp. 77 679–77 688, 2023.
  - [7] A. A. Barakabitze, M. Liyanage, and A. Hines, "QoESoft: QoE Management Architecture for Softwarized 5G Networks," in *2020 IEEE International Conference on Communications Workshops (ICC Workshops)*, 2020, pp. 1–6.
  - [8] B. Agarwal, M. A. Togou, M. Ruffini, and G.-M. Muntean, "QoE-Driven Optimization in 5G O-RAN-Enabled HetNets for Enhanced Video Service Quality," *IEEE Communications Magazine*, vol. 61, no. 1, pp. 56–62, 2023.
  - [9] T. Hossfeld, M. Varela, L. Skorin-Kapov, and P. E. Heegaard, "A Greener Experience: Trade-offs between QoE and CO2 Emissions in Today's and 6G Networks," *IEEE Communications Magazine*, pp. 1–7, 2023.
  - [10] G. Bingol, T. Hossfeld, and C. Timmerer, "Sustainability vs. Quality of Experience: Striking the Right Balance for Video Streaming," *ACM SIGMultimedia Rec.*, 2023. [Online]. Available: <https://records.sigmm.org/2023/04/11/sustainability-vs-quality-of-experience-striking-the-right-balance-for-video-streaming/>
  - [11] T. Hofffeld, M. Varela, L. Skorin-Kapov, and P. E. Heegaard, "What is the Trade-Off Between CO2 Emission and Video-Conferencing QoE?" *ACM SIGMultimedia Rec.*, vol. 14, no. 1, oct 2023.
  - [12] M. Fiedler, A. Popescu, and Y. Yao, "QoE-Aware Sustainable Throughput for Energy-Efficient Video Streaming," in *2016 IEEE International Conferences on Big Data and Cloud Computing (BDCloud), Social Computing and Networking (SocialCom), Sustainable Computing and Communications (SustainCom)*, 2016, pp. 493–500.
  - [13] G. Bingöl, A. Floris, S. Porcu, C. Timmerer, and L. Atzori, "Are Quality and Sustainability Reconcilable? A Subjective Study on Video QoE, Luminance and Resolution," in *2023 15th International Conference on Quality of Multimedia Experience (QoMEX)*, 2023, pp. 19–24.
  - [14] ETSI, "5G; NR; physical layer procedures for data (3GPP TS 38.214 version 16.2.0 Release 16)," 2020.
  - [15] E. F. Pupo, C. C. González, J. Montalban, P. Angueira, M. Murrioni, and E. Iradier, "Artificial Intelligence Aided Low Complexity RRM Algorithms for 5G-MBS," *IEEE Transactions on Broadcasting*, 2023.
  - [16] C. C. González, E. F. Pupo, L. Atzori, and M. Murrioni, "Dynamic Radio Access Selection and Slice Allocation for Differentiated Traffic Management on Future Mobile Networks," *IEEE Transactions on Network and Service Management*, vol. 19, no. 3, pp. 1965–1981, 2022.
  - [17] C. C. González, E. F. Pupo, E. Iradier, P. Angueira, M. Murrioni, and J. Montalban, "Network Selection over 5G-Advanced Heterogeneous Networks Based on Federated Learning and Cooperative Game Theory," *IEEE Transactions on Vehicular Technology*, pp. 1–16, 2024.
  - [18] E. F. Pupo, C. C. González, E. Iradier, J. Montalban, and M. Murrioni, "5G Link-Level Simulator for Multicast/Broadcast Services," in *2023 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB)*. IEEE, 2023, pp. 1–6.
  - [19] N. Chukhno, O. Chukhno, S. Pizzi, A. Molinaro, A. Iera, and G. Araniti, "Efficient management of multicast traffic in directional mmWave net-