360° Mulsemedia Experience over Next Generation Wireless Networks - A Reinforcement Learning Approach

Ioan-Sorin Comșa†, Ramona Trestian‡ and Gheorghiță Ghinea†
†Department of Computer Science, Brunel University London, Kingston Lane, UB8 3PH, London, U.K.
‡Faculty of Science and Technology, Middlesex University, NW4 4BT, Hendon, London, U.K.
E-mails: ioan-sorin.comsa@brunel.ac.uk, r.trestian@mdx.ac.uk, george.ghinea@brunel.ac.uk

Abstract—The next generation of wireless networks targets aspiring key performance indicators, like very low latency, higher data rates and more capacity, paving the way for new generations of video streaming technologies, such as 360° or omnidirectional videos. One possible application that could revolutionize the streaming technology is the 360° MULtiple SEnsorial MEDIA (MULSEMEDIA) which enriches the 360° video content with other media objects like olfactory, haptic or even thermoceptic ones. However, the adoption of the 360° Mulsemedia applications might be hindered by the strict Quality of Service (QoS) requirements, like very large bandwidth and low latency for fast responsiveness to the user′s inputs that could impact their Quality of Experience (QoE). To this extent, this paper introduces the new concept of 360° Mulsemedia as well as it proposes the use of Reinforcement Learning to enable QoS provisioning over the next generation wireless networks that influences the QoE of the end-users.

Index Terms—QoE, mulsemedia, omnidirectional video, reinforcement learning, packet scheduling, network optimization.

I. Introduction

The main challenge within the current and future wireless networks environments is to achieve higher users′ satisfaction by providing faster and reliable networks and to enable Quality of Experience (QoE) for the end-users′ main activities. The growing popularity of the new multimedia-rich immersive applications puts significant pressure over the underlying wireless networks. As QoE will become the main differentiator between network operators, it is imperative for them to come up with innovative solutions that will accommodate all these bandwidth-hungry applications while maintaining high user perceived quality levels [1].

Stimulated by this tremendous need to enhance the multimedia experience for the end-users, interactive 360° video streaming became very popular in Virtual Reality (VR) systems, where users explore 360° views of the captured scenes [2]. Currently, 360° video content is provided by professional content providers (i.e. NBC, CNN) and user-generated content platforms such as Google, Facebook and Youtube [2]. Following this ambitious trend, it can be envisioned that a new class of applications that could revolutionize the streaming technology is the 360° MULtiple SEnsorial

MEDIA (MULSEMEDIA) [3]. Mulsemedia enables the integration of other human senses into the human-computer interaction. Thus, 360° video applications could integrate additional 360° sensory media content (e.g., ofactory, haptic or thermoceptics media objects) that could eventually enable even better quality of user experience [4]. However, the new 360° mulsemedia services would come at the cost of more bandwidth than other conventional applications [5] and stringent delay requirements [6]. In this context, innovative solutions are needed to enable Quality of Service (QoS) and QoE provisioning when delivering 360° mulsemedia services over next generation wireless networks.

One possible solution to minimize the application delay is to bring the 360° mulsemedia content closer to the mobile User Equipment (UE) by integrating a Mobile Edge Computing (MEC) server at the serving Base Station (BS) [7] or by increasing the network density to enhance multipath delivery [8]. Additionally, higher data rates can be supported by adopting new waveforms and higher frequency bands in the radio access scheme [9]. However, no matter how large the system bandwidth is, the Radio Resource Management (RRM) still remains an open research issue especially when delivering 360° mulsemedia content within a multi-user scenario.

In this context, this paper introduces a new concept application referred to as 360° Mulsemedia and proposes the use of Reinforcement Learning (RL) within RRM to enable QoS provisioning over next generation wireless networks. It is shown that by integrating RL into the RRM 5G Scheduler to select the best scheduling rule according to the dynamics of network conditions, the users′ satisfaction in terms of QoS can be significantly improved.

II. Related Work

Extensive studies on QoE performances when delivering 360° video content are provided in [10]–[12]. It can be concluded that the user′s perceived quality depends on different factors, such as: encoder parameters, multimedia content characteristics and device type. Moreover, the study presented in [10] reveals high correlations between Peak Signal to Noise Ratio (PSNR) and perceptual quality. Nasrabadi et al. [13] propose a layered encoding scheme for 360° video delivery that reduces the probability of video freezes and the response latency to head movements. To reduce the bandwidth utilization, some proposals adopt 360° video adaptation
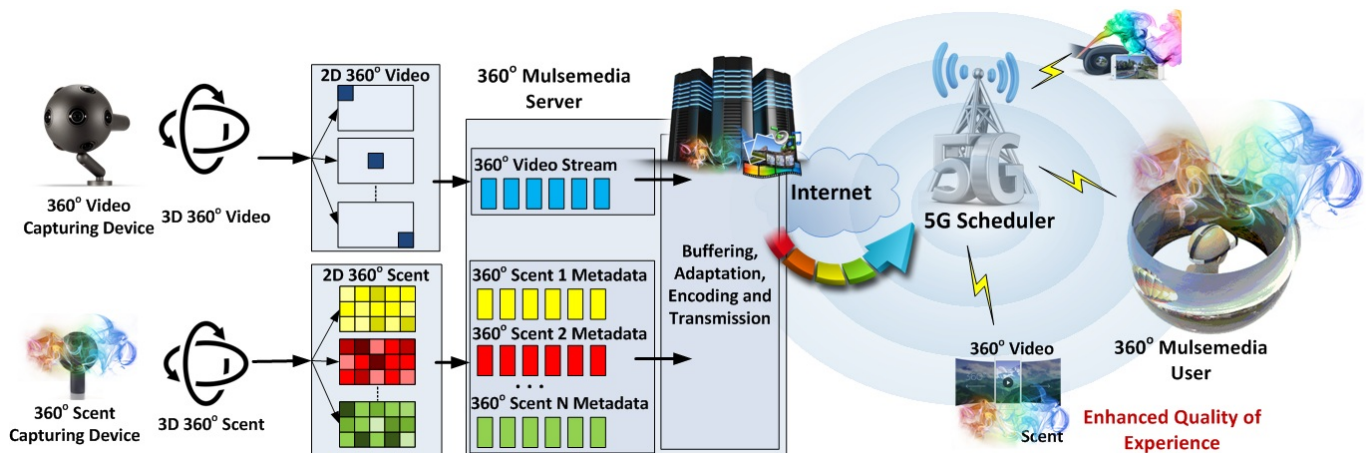
Fig. 1 360° Mulsemedia Delivery System

techniques [14] or motion-based predictive solutions [15], [16]. The perceptual 360° video quality can be improved if the encoder parameters, modulation/coding scheme allocation and the relay selection are jointly optimized, as stated in [7].

Studies on QoE performance when considering additional sensory objects to classical video services are provided in [17]. The synchronization between multiple media components such as 2D video, haptic and airflow is analyzed in [18] by measuring the Mean Opinion Score (MOS) for the perceived sense of relevance, reality, distraction, annoyance and enjoyment. In [19], the user perceived QoE denotes that the mulsemedia objects can only partially mask the decrease in movie quality. An adaptive mulsemedia framework at the server side is proposed in [20] which outperforms the existing multimedia delivery solutions in terms of user perceived quality and user enjoyment.

Despite the amount of research done in this area, none of the presented solutions considers the 360° mulsemedia applications and the delivery challenges within next generation wireless networks. In this sense, the packet scheduler plays a crucial role when allocating the radio resources to 360° mulsemedia users. Some of the well known schedulers are: Barrier Function (BF) guarantees certain bit rates requirements, the EXPonential (EXP) rule minimizes the packet delay and the Opportunistic Packet Loss Fair (OPLF) improves the Packet Loss Rate (PLR) performance [21]. Using these schedulers independently they could improve on one criteria only (e.g., packet delay, PLR, etc.). However, if these schedulers are combined such that the best rule is selected based on the dynamics of network conditions, the users′ QoS satisfaction can be significantly improved. Thus, this paper proposes the use of Reinforcement Learning for scheduling 360° mulsemedia traffic over next generation networks. Based on the RL approach, the framework is able to learn the most convenient scheduler to be used each time, such that, the QoS satisfaction is maximized. RL approach shows its utility when scheduling conventional traffic types under different QoS objectives [22].

The main contributions of this paper are as follows:
1) 360° Mulsemedia Traffic Concept: the concept of 360° Mulsemedia Traffic is introduced where multiple sensory objects are added to the conventional 360° video content to improve the performance of end-users′ QoE indicators.
2) Mapping 360° Olfactory Media Objects: a method that maps multiple 360° olfactory senses to the existing 360° video content is introduced.
3) 360° Mulsemedia Scheduler based on RL Approach: a RL approach for scheduling 360° mulsemedia traffic that improves the QoS in terms of Guaranteed Bit Rate (GBR), delay and PLR requirements is presented.

III. 360° MULSEMEDIA DELIVERY SYSTEM

Figure 1 depicts the proposed 360° mulsemedia delivery system. At the server side, alongside the 360° video capturing device, a 360° scent capturing device is also able to collect various olfactory types associated with the video representation. The 360° mulsemedia server has several functionalities such as: 360° olfactory objects mapping, 360° media objects synchronization, buffering, adaptation, encoding and transmission. The 360° mulsemedia content is transmitted to the 360° mulsemedia user over the 5G wireless networks. The performance of the 5G radio scheduler depends on the number of 360° mulsemedia users, mobility, positioning, channel conditions, etc.

User accesses the 360° mulsemedia content on mobile terminals or Head-Mounted Display (HMD) devices enhanced with olfactory diffuser capabilities. At a certain time, only the scene that the user is facing is displayed, which is a fraction from the whole downloaded content. The proposed delivery system should be able to react to the head movements as well to the HMD refreshing rate with a latency of less than 10ms to assure acceptable QoE performance [6].

Unlike traditional video delivery systems, in VR systems, the entire 360° video stream is sent to the user and its HMD device extracts the viewport content according to the head position. To minimize the bandwidth waste, one of the viewport-adaptive streaming solution could be used where only the content quality inside users viewport is maximized, and the rest of the content is sent at a lower quality level [6]. In this way, the GBR requirements for the obtained traffic are much lower than the original 360° video traffic. If the proposed multimedia system is not able to assure the stringent delay requirements, users can still experience other scenes from the 360° video at lower qualities.
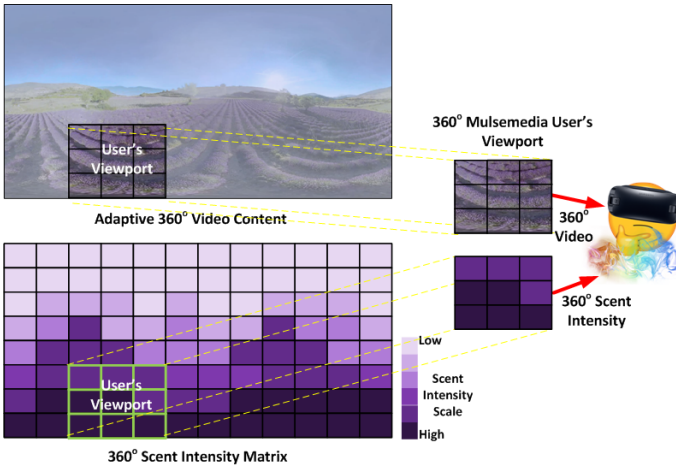
Fig. 2 Mapping 360° Scents Object to 360° Video Content

However, one way to avoid this drawback that can seriously degrade the QoE performance is the use of additional 360° olfactory media objects synchronized and transmitted along with the 360° video content. The 360° olfactory media objects are mapped into an 360° olfactory intensity scale corresponding to the respective 360° video content regions. This solution could eventually improve the user′s overall QoE even when experiencing poor video quality due to fast head movements and unfavorable network conditions.

A. Mapping 360° Olfactory Media Objects to 360° Video

Among all existing representations of the captured spherical videos, we use the equirectangular view since the current video encoders operate on two-dimensional rectangular images [6]. According to this representation, the panoramic video is divided into equirectangular tiles. Each tile represents a given viewport that has typically a viewing angle of 120°.

The captured 360° scent information should be divided in exactly the same number of tiles as the 360° video panorama. Each tile from the captured scent matrix provides a given scent intensity for the corresponding viewport. The assignation procedure of the scent tiles to the panoramic image is called mapping. Figure 2 illustrates an example scenario of the reception procedure for a 360° mulsemedia content illustrating a lavender field. Based on the perfect mapping between the 360° video content and the scent tiles, the end-user will experience the high quality of the viewport together with the lavender scent at the corresponding intensity level depending on its position and the current view. The viewport content together with the neighboring tiles are transmitted at the highest quality, while the rest of the video content at a much lower quality. For the lavender olfactory sense, the whole matrix of intensities is transmitted and reproduced at the reception. This characteristic may enable higher QoE performance when poor video quality is experienced due to very fast changes of users′ viewports.

B. 360° Mulsemedia Server

Each tile from the scent intensity frames is encoded in data packets. The tile packet of each scent contains the fields as shown in Table I. The headers for each scent are grouped to meta-data format and synchronized with the video packets.

Table I. Packet Header for the Scent Tile

Name	Size	Description
Type	1 Byte	Define the type of captured scent
Sequence Number	2 Bytes	Increments by one each time when the scent intensity matrix is sent
Tile No.	1 Byte	Denotes the tile number from the scent matrix
Start Time	4 Bytes	The start time of the scent
Duration	4 Bytes	Duration of the scent synchronized with the video packet
Intensity	2 Byte	Denotes the scent intensity (many quantization levels may be used)

Due to the bandwidth limitations, the 360° mulsemedia content needs to be adapted in order to keep a minimum level for the QoE satisfaction. In this regard, a modified version of Dynamic Adaptive Streaming over HTTP (DASH) [6] for 360° mulsemedia delivery could be integrated. The server takes as input the 360° mulsemedia content and converts each frame in equirectangular layouts. The server creates N number of 360° video versions with different Quality Emphasized Regions (QERs). The QER represents the region of the mulsemedia data with the improved content quality than the rest of the content. Each of these representations, is encoded in K versions at different bit rates. Then, these versions are grouped into $N \times K$ segments in order to enhance users′ QoE when switching from one representation to another when necessary according to the network conditions and viewport position. The scent intensity matrices are sent together with the video frames regardless of the segment representation.

Based on the viewport center, the user selects the most convenient QER of the video. According to the selected QER and bandwidth estimation over a t milliseconds period, the most appropriate encoding rate for the video frames is selected. Based on the requested representation, the server sends the video content together with the assigned scent intensity information. When the channel conditions are extremely poor (requesting low encoding rates), the user may request the server to eliminate certain scents in order to keep an acceptable QoE performance. In this context, the server can take one of the three actions: *a)* deliver the video content and scent data with maximum quality when users experience very good channel conditions; *b)* degrade the QER video quality while delivering the scent data; *c)* degrade both QER video quality and scent data. After selecting the segment representation, the video and scent data packets are encoded into mulsemedia packets and transmitted to the end-users.

C. 5G Scheduler for 360° Mulsemedia Delivery

The role of the 5G packet scheduler is to allocate the available frequency spectrum to mulsemedia users in such a way that the overall QoS satisfaction measure is maximized. In general, the packet scheduler works with different dispatching or scheduling rules. Each rule prioritizes certain users based on some input information, such as: device types, user profiles, 360° mulsemedia characteristics. A major drawback of these rules refers to the inability to adapt to changeable

and unpredictable network conditions. In this situation, only some particular QoS objectives are addressed, and the overall QoS satisfaction is degraded. However, one way to overcome this major drawback is to propose a framework able to select according to the actual network conditions and 360° mulsemedia traffic characteristics, the best scheduling rule in such a way that the overall QoS satisfaction is maximized. To make this solution tractable in real time scheduling systems, we propose a solution based on the Reinforcement Learning framework which is able to learn the best rule to be applied based on the instant scheduler states.

IV. RL APPROACH FOR 360° MULSEMEDIA SCHEDULING

In frequency domain, the available bandwidth is divided in equal Resource Blocks (RBs), the smallest frequency resources that are allocated by each BS to end-users as illustrated in Fig. 3. We define an user equipment being characterized by 360° mulsemedia traffic with stringent QoS requirements in terms of packet delay, throughput, packet loss, jitter, fairness, etc. The packet scheduler is characterized by various scheduling rules and each rule is addressing only on a specific QoS objective. The scheduling procedure is achieved at each Transmission Time Interval (TTI) of 1 ms, a time window in which the user requests are sent to the server and the mulsemedia packets are scheduled in the frequency domain over the 5G radio access networks.

A. Problem Formulation

We denote by $\mathcal{B} = \{1, 2, ..., B\}$ the set of RBs corresponding to a given system bandwidth and $\mathcal{U} = \{1, 2, ..., U\}$ the set of active users requesting 360° mulsemedia content. The role of packet scheduler is to share the disposable set $\mathcal{B}$ to mulsemedia users. Furthermore, we define the set of QoS objectives $\mathcal{O} = \{1, 2, ..., O\}$. It is said that a certain QoS objective is satisfied, when the corresponding indicator satisfies its requirement being specified for the 360° mulsemedia traffic. The packet scheduler works with a finite set of scheduling rules $\mathcal{R} = \{1, 2, ..., R\}$. A given rule $r \in \mathcal{R}$ favors the satisfaction of only one objective $o \in \mathcal{O}$. According to the chosen rule, $U \times B$ ranking values are determined each TTI, where each value provides a measure of how necessary is the allocation of a given RB $b \in \mathcal{B}$ to user $u \in \mathcal{U}$ from the perspective of QoS objective $o \in \mathcal{O}$. Then, the packet scheduler selects the user with the highest metric for each RB. However, in this way, the satisfaction of objective $o \in \mathcal{O}$ is maximized, while harming other ones $\mathcal{O} \setminus \{o\}$ when the same rule is applied for the entire downlink scheduling session.

We propose the use of an innovative scheduling scheme able to apply at each TTI a different rule in such a way that the satisfaction of all scheduling objectives $\mathcal{O}$ is maximized over time. In order to achieve this goal, we need to know in advance which rule fits best at each TTI under certain momentary networking conditions. By searching the best solution at each TTI, it will increase the system complexity that is unacceptable when scheduling 360° mulsemedia traffic in real time. Thus, we propose a RL framework that is able to interact with the RRM environment and learn over time the best rule to be selected for each scheduler state.
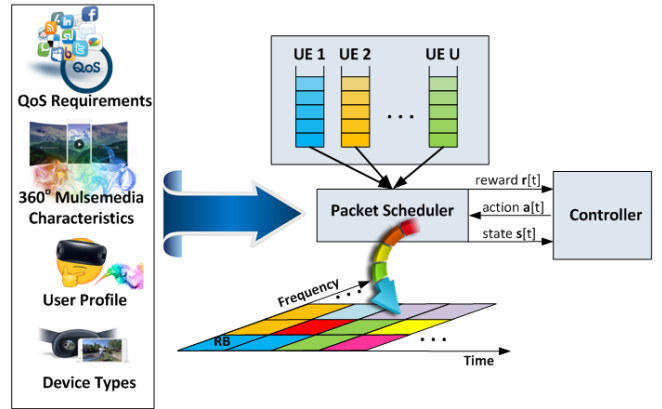

Fig. 3 Packet Scheduler Based on Proposed RL Framework

B. RL Framework

The idea behind this approach is to obtain a scheduling policy, that decides for each scheduler state which is the best rule to be applied. In this sense, the RL framework uses an intelligent controller that interacts with the 5G scheduler to learn the optimal scheduling policy as shown in Fig. 3. When using this policy to real time scheduling systems, the function that measures the overall QoS performance for all objectives is maximized. This function is used by the RL algorithm to update some quality values of selecting the rules in each state. When the QoS satisfaction decreases from one TTI to another, it is unlikely to use again the same rule for that state.

At each TTI t, the controller observes the scheduler *state* and takes an *action* randomly or according to the state-action experiences which were met so far. The scheduling procedure is conducted based on the decided *action*. At $t + 1$, the controller perceives a new state and an associated *reward* value, which evaluates the previous selected action in terms of QoS satisfaction. The controller iterates from a state to another, explores all possible state-action pairs until the scheduling policy converges according to certain criteria.

1) States: Let us consider $\mathcal{S}$ the finite and multidimensional set for the scheduler state space. The momentary scheduler state at TTI t, $\mathbf{s}[t] \in \mathcal{S}$ may contain the following parameters: number of 360° mulsemedia users, channel conditions, QoS indicators and requirements, arrival rates, queue lengths, 360° mulsemedia traffic characteristics, device types, etc. When the number of users increases, the dimension of momentary states becomes very high. Some compressions techniques can be used in this sense to avoid the dependency on the number of users. Then, the states can be discretized by using neural networks as function approximations [22].

2) Actions: We define the discrete action space as $\mathcal{A} = \{a_1, a_2, ..., a_R\}$. At each TTI t, the controller selects an action based on some exploration probabilities. If the current action is $\mathbf{a}[t] = a_r$, then the applied scheduling rule is $r \in \mathcal{R}$.

3) Rewards: The reward value aims to evaluate how good is the action $\mathbf{a}[t] = a_r$ applied in state $\mathbf{s}[t] = \mathbf{s}$ from the viewpoint of overall QoS satisfaction. This value is calculated in the next scheduler state $\mathbf{s}[t + 1] = \mathbf{s}' \in \mathcal{S}$ according to the reward function $\mathbf{r} : \mathbb{R}^{O \times U} \to \mathbb{R}$, being expressed as follows:

$$\mathbf{r}(\mathbf{x}) = \sum_o \sum_u \mathbf{r}_{o,u}(\mathbf{x}_{o,u}) \tag{1}$$

where, $\mathbf{x}_{o,u}[t] = \mathbf{x}_{o,u}$ is the QoS vector for objective $o \in \mathcal{O}$ corresponding to user $u \in \mathcal{U}$ and $\mathbf{x} = [\mathbf{x}_{o,1}, ..., \mathbf{x}_{o,U}]$. In particular, the reward function for each objective $o \in \mathcal{O}$ and user $u \in \mathcal{U}$, $\mathbf{r}_{o,u}(\mathbf{x}_{o,u})$, can be defined based on 360° mulsemedia traffic requirements and characteristics.

4) Algorithms: When the reward value $\mathbf{r}(\mathbf{x})$ calculated in state $\mathbf{s}' \in \mathcal{S}$ reveals high QoS satisfaction, we encourage to apply the same action $a_r \in \mathcal{A}$ when the same scheduler state $\mathbf{s} \in \mathcal{S}$ is observed in future. Otherwise, we decrease the probability value of selecting that rule on that particular state. The way the state-action value is updated determines the type of RL algorithm being used. Studies in [23], [24] reveal that the Actor-Critic (AC) schemes are the best options when learning the scheduling policies for the fairness objective. In [22], the proposed AC scheme is able to obtain good convergence properties when scheduling different traffic types. This RL AC scheme aims to update the state-action $(\mathbf{s}, a_r)$ value only if the applied action $a_r \in \mathcal{A}$ is a good option according to the critic decision. Based on these results, we use the same RL AC scheme when scheduling 360° mulsemedia traffic.

V. RESULTS AND DISCUSSIONS

In order to demonstrate the suitability of integrating the RL Actor-Critic framework when scheduling 360° mulsemedia traffic, this section presents a case study as a proof-of-concept. The case study considers four types of traffic, such as: video traffic with 138kbps and 242kbps, Constant Bit Rate (CBR) traffic at 640kbps and Variable Bit Rate Traffic with the mean of 1024kbps. The QoS requirements for these traffic types can be found in [22], where $O = 3$. The aim is to learn a scheduling policy for each of these traffic types by using the RL AC framework that mixes three scheduling rules ($R = 3$): (1) BF with the main focus on bit rate requirements, (2) EXP that prioritize UEs with higher packet delay and (3) OPLF with the main focus on packet loss minimization.

An OFDMA downlink transmission is considered with $B = 100$ RBs. A number of $U = 240$ users are generating video traffic at 138kbps, $U = 120$ users are generating video traffic at 242kbps, and each CBR and VBR traffic load is characterized by a number of $U = 50$ users. We perform the RL AC framework for each of these traffic classes separately. Then, each traffic policy is trained for 10^7ms, where the number of users is changing at different moments in the learning stage in order to experience as many observations from $\mathcal{S}$ as possible. The user speed is 30kmph and the mobility model is random direction. When exploiting the learned policies, we analyze all traffic load settings with static user positions uniformly distributed within the central cell for about 50s. Then, we average the obtained performance indicators for each traffic type and load settings.

We measure the performance of the obtained scheduling policies in the exploitation stage by considering the average number of TTIs when all active users satisfy the QoS requirements for each traffic type. Figure 4 presents the set of simulation results obtained when learning the scheduling policies for each traffic type by using the AC RL algorithm and mixing the considered set of scheduling rules compared to the case where each rule is used independently. When

guaranteeing the bit rates requirements, as expected, the BF scheduling rule achieves the best performance, being followed by the proposed AC policy. OPLF can also achieve good level of bit rate satisfaction due to its capability of decreasing the packet drop rates, especially for higher bit rates traffic types. For the delay satisfaction, the EXP rule achieves the best performance for each traffic type. The proposed AC policy is the second best choice when achieving these particular objectives for the packet delay requirements. The proposed AC scheme achieves the best performance when the PLR minimization is taken into account. When compared to OPLF or EXP rule, this gain is explicable since the AC policy is able to predict better the errors in the wireless channels. The OPLF rule aims to schedule users with higher PLRs even if the errors in the wireless channel persist for longer time. However, when the requirements for GBR, PLR and delay are jointly analyzed, the proposed actor-critic framework provides the best performances for all traffic types, achieving maximum gains of 15% compared to EXP and OPLF schemes and 75% with the respect of BF scheduling rule.

As shown in Fig. 4, the AC policy is able to achieve much better performance when mixing properly the BF, OPLF and EXP rules at different TTIs for traffic types with various arrival rates, QoS requirements and traffic loads. The learned AC policies are able to achieve higher gains for users' satisfaction measure when increasing the traffic data rates.

It can be concluded that the proposed AC RL scheme is very promising when considering to schedule 360° mulsemedia traffic in next generation wireless and cellular networks, where much higher data rates are required with minimal delay and packet loss for an improved QoE.

VI. CONCLUSIONS

In this paper, we introduce the concept of 360° mulsemedia, where additional 360° olfactory, haptic, thermoceptics media objects are added to the 360° video content to improve the end-users' QoE. A standard procedure of mapping the additional 360° media objects to 360° video such that the obtained 360° mulsemedia content has all sensory components synchronized, is described. Moreover, when scheduling multiple 360° mulsemedia users over cellular networks, the Reinforcement Learning approach could be used at the 5G scheduler enabling the selection of the most convenient scheduling rule according to the momentary network conditions such that, the overall QoS user satisfaction is maximized. Simulation results show that the RL Actor-Critic approach is a promising solution that could be used for maximizing the QoS user satisfaction when scheduling 360° mulsemedia traffic with high data rates and stringent delay requirements.

Future works will study the impact of packet loss on the perceived 360° mulsemedia QoE through subjective tests.

REFERENCES

[1] R. Trestian, I.-S. Comşa, and M. F. Tuysuz, "Seamless Multimedia Delivery within a Heterogeneous Wireless Networks Environment: Are We There Yet?"*in IEEE Communications Surveys and Tutorials*, vol. PP, no. 99, pp. 1–1, 2018.

[2] C. Zhou, Z. Li, and Y. Liu, "A Measurement Study of Oculus 360 Degree Video Streaming,"*in Proceedings of the 8th ACM on Multimedia Systems Conference*, June 2017, pp. 27 – 37.
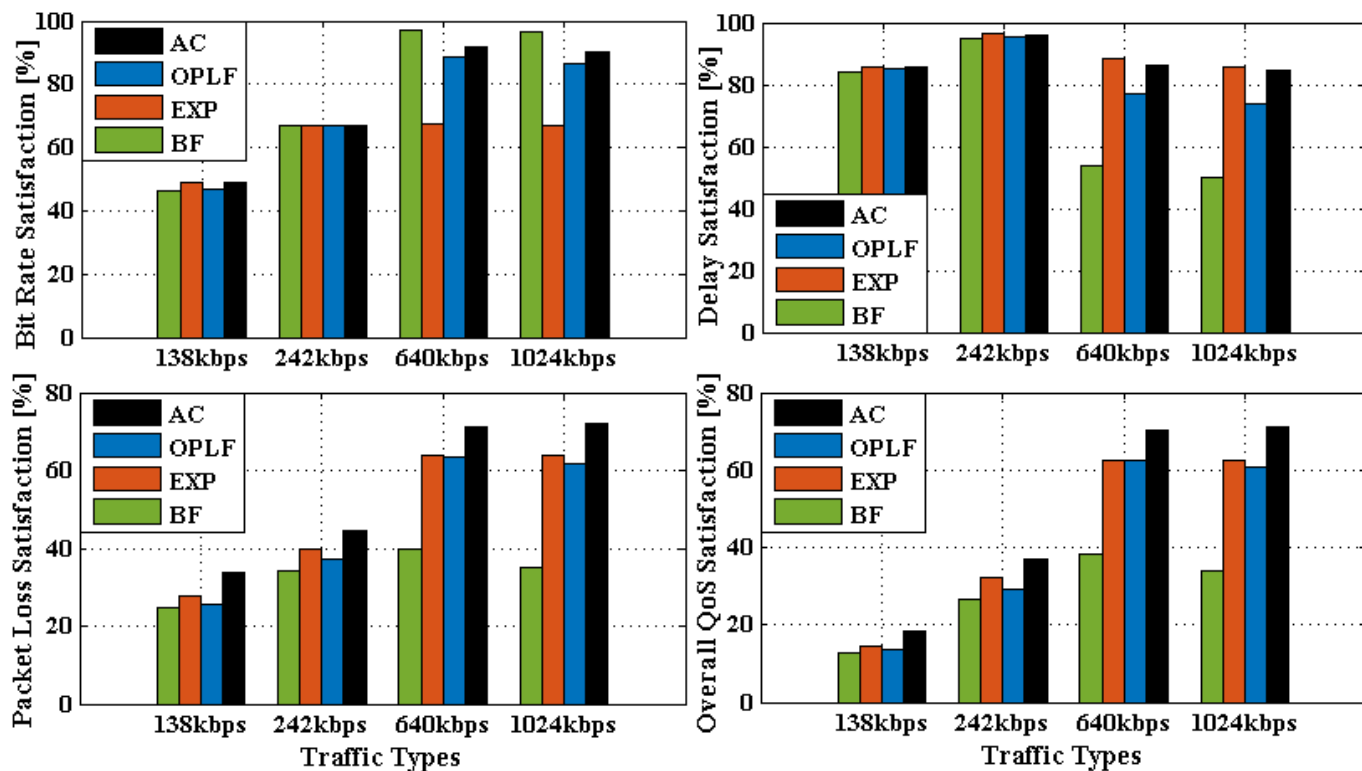
Fig. 4 Simulation Results based on RL Actor-Critic Framework

[3] G. Ghinea, C. Timmerer, W. Lin, and S. R. Gulliver, "Mulsemedia: State of the Art, Perspectives, and Challenges,"*in ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, vol. 11, no. 17, pp. 17:1–17:23, 2014.

[4] O. A. Ademoye and G. Ghinea, "Information Recall Task Impact in Olfaction-Enhanced Multimedia,"*in ACM Transactions on Multimedia Computing, Communications and Applications (TOMM)*, vol. 9, no. 3, pp. 17:1–17:16, 2013.

[5] T.-M. Liu, C.-C. Ju, Y.-H. Huang, T.-S. Chang, K.-M. Yang, and Y.-T. Lin, "A 360-Degree 4K x 2K Panoramic video Processing Over Smartphones,"*in IEEE International Conference on Consumer Electronics (ICCE)*, January 2017, pp. 1–3.

[6] X. Corbillon, G. Simon, A. Devlic, and J. Chakareski, "Viewport-Adaptive Navigable 360-Degree Video Delivery,"*in IEEE International Conference on Communications (ICC)*, May 2017, pp. 1–7.

[7] K. Liu, Y. Liu, J. Liu, and A. Argyriou, "Joint Source Encoding and Networking Optimization for Panoramic Video Streaming over LTE-A Downlink,"*in IEEE Global Communications Conference (GLOBE-COM)*, December 2017, pp. 1–7.

[8] X. Ge, L. Pan, Q. Li, G. Mao, and S. Tu, "Multipath Cooperative Communications Networks for Augmented and Virtual Reality Transmission,"*in IEEE Transactions on Multimedia*, vol. 19, no. 10, pp. 2345–2358, 2017.

[9] J. G. Andrews, S. Buzzi, W. Choi, S. V. Hanly, A. Lozano, A. C. K. Soong, and J. C. Zhang, "What Will 5G Be?"*in IEEE Journal on Selected Areas in Communications (JSAC)*, vol. 32, no. 6, pp. 1065 – 1082, 2014.

[10] H. T. T. Tran, N. P. Ngoc, C. M. Bui, M. H. Pham, and T. C. Thang, "An Evaluation of Quality Metrics for 360 Videos,"*in Ninth International Conference on Ubiquitous and FutureNetworks*, July 2017, pp. 1–5.

[11] H. T. T. Tran, N. P. Ngoc, C. T. Pham, Y. J. Jung, and T. C. Thang, "A Subjective Study on QoE of 360 Video for VR Communication,"*in IEEE 19th International Workshop on Multimedia Signal Processing (MMSP)*, October 2017, pp. 1–6.

[12] R. Schatz, A. Sackl, C. Timmerer, and B. Gardlo, "Towards Subjective Quality of Experience Assessment for Omnidirectional Video Streaming,"*in Ninth International Conference on Quality of Multimedia Experience (QoMEX)*, July 2017, pp. 1–6.

[13] A. Taghavi Nasrabadi, A. Mahzari, J. D. Beshay, and R. Prakash, "Adaptive 360-Degree Video Streaming using Layered Video Coding,"*in IEEE Virtual Reality (VR)*, March 2017, pp. 1–2.

[14] M. Budagavi, J. Furton, G. Jin, A. Saxena, J. Wilkinson, and A. Dicker-son, "360 Degrees Video Coding using Region Adaptive Smoothing,"*in IEEE International Conference on Image Processing (ICIP)*, September 2015, pp. 750–754.

[15] Y. Bao, T. Zhang, A. Pande, H. Wu, and X. Liu, "Motion-Prediction-Based Multicast for 360-Degree Video Transmissions,"*in IEEE International Conference on Sensing, Communication, and Networking (SECON)*, June 2017, pp. 1–9.

[16] F. Qian, L. Ji, B. Han, and V. Gopalakrishnan, "Optimizing 360 Video Delivery over Cellular Networks,"*in Proceedings of the 5th Workshop on All Things Cellular: Operations, Applications and Challenges*, December 2017, pp. 1–6.

[17] N. Murray, O. A. Ademoye, G. Ghinea, Y. Qiao, G.-M. Muntean, and B. Lee, "Olfactory-enhanced Multimedia Video Clips Datasets,"*in Ninth International Conference on Quality of MultimediaExperience (QoMEX)*, June 2017, pp. 1–5.

[18] Z. Yuan, T. Bi, G.-M. Muntean, and G. Ghinea, "Perceived Synchronization of Mulsemedia Services,"*in IEEE Transactions on Multimedia*, vol. 17, no. 7, pp. 957–966, 2015.

[19] Z. Yuan, G. Ghinea, and G.-M. Muntean, "Quality of Experience Study for Multiple Sensorial Media Delivery,"*in International WirelessCommunications and Mobile Computing Conference (IWCMC)*, August 2014, pp. 1142–1146.

[20] Z. Yuan, G. Ghinea, and G. M. Muntean, "Beyond Multimedia Adaptation: Quality of Experience-Aware Multi-Sensorial Media Delivery,"*in IEEE Transactions on Multimedia*, vol. 17, no. 1, pp. 104–117, 2015.

[21] F. Capozzi, G. Piro, L. A. Grieco, G. Boggia, and P. Camarda, "Downlink Packet Scheduling in LTE Cellular Networks: Key Design Issues and a Survey,"*in IEEE Communications Surveys Tutorials*, vol. 15, no. 2, pp. 678 – 700, 2013.

[22] I.-S. Comşa, A. De Domenico, and D. Ktenas, "QoS-Driven Scheduling in 5G Radio Access Networks - A Reinforcement Learning Approach,"*in IEEE Global Communications Conference (GLOBE-COM)*, December 2017, pp. 1–7.

[23] I.-S. Comşa, M. Aydin, S. Zhang, P. Kuonen, J.-F. Wagen, and Y. Lu, "Scheduling Policies Based on Dynamic Throughput and Fairness Tradeoff Control in LTE-A Networks,"*in IEEE Local Computer Networks (LCN)*, September 2014, pp. 418–421.

[24] I.-S. Comşa, S. Zhang, M. Aydin, J. Chen, P. Kuonen, and J.-F. Wagen, "Adaptive Proportional Fair Parameterization Based LTE Scheduling Using Continuous Actor-Critic Reinforcement Learning,"*in IEEE Global Communications Conference (GLOBECOM)*, December 2014, pp. 4387–4393.