QoE-Aware Resource Allocation for Multiple Cloud Gaming Users Sharing a Bottleneck Link

Slivar, Ivan; Skorin-Kapov, Lea; Sužnjević, Mirko

QoE-Aware Resource Allocation for Multiple Cloud Gaming Users Sharing a Bottleneck Link

Ivan Slivar, Lea Skorin-Kapov, Mirko Suznjevic
University of Zagreb, Faculty of Electrical Engineering and Computing
Zagreb, Croatia
{ivan.slivar, lea.skorin-kapov, mirko.suznjevic}@fer.hr

***Abstract*—Cloud gaming offers the capability of delivering high-quality graphics games to any type of end user device, however at the cost of high bandwidth consumption and strict latency requirements. Meeting Quality of Experience (QoE) requirements under limited resource availability calls for efficient and dynamic service adaptation. In this paper, we formulate an optimization problem for QoE-aware resource allocation for multiple cloud gaming users sharing a bottleneck link. The optimization problem is solved by utilizing algorithms that employ QoE estimation models derived from subjective studies for different types of games. We specifically investigate the impact on the resource allocation outcome when jointly considering both quality and QoE fairness as optimization objectives. The QoE-aware algorithms are shown to achieve higher average and higher minimum MOS values compared to a baseline algorithm. Results also confirm that both a cloud gaming service provider and resource provider should consider game type when adapting video coding parameters and allocating resources.**

***Index Terms*—cloud gaming QoE, QoE modelling, resource allocation**

I. Introduction

Providing different types of content "on demand" anywhere and on any device has been a dominant market trend for networked services in recent years. When it comes to games, this paradigm is implemented through "cloud gaming", whereby game content is delivered from a server to a client in the form of a video stream. The execution of the game logic, rendering of the 3D virtual scene, and video encoding are performed at the server, while the client is responsible for video decoding and capturing of client input.

Network flows generated by cloud gaming require significant network bandwidth and have very strict latency requirements (e.g., Nvidia's GeForce NOW requires bandwidth up to 50 Mbit/s and round trip time (RTT) from client to the server lower then 60 ms[1]). The availability of network bandwidth might vary over time, thus most cloud gaming services implement some type of service adaptation algorithm which adjusts the video codec parameters accordingly. Adaptation mechanisms used by the GeForce NOW service have been studied in detail in [1]. While such adaptation algorithms consider a per-game-flow perspective, we consider the case of multiple game flows which share a common network path subject to bandwidth constraints. Jointly optimized adaptation across multiple flows may lead to improved resource utilization, distribution of available bandwidth in a fair manner, and potential increase in overall Quality of Experience (QoE) for involved gamers [2].

With regards to QoE influence factors, a large number of studies have focused on the impacts of latency and/or packet loss on user perceived quality [3]–[14], while fewer studies have addressed the impact of different video encoding configurations on QoE [2], [8], [14]–[17]. In our previous work, we presented the results of conducted subjective studies that focused on measuring and modeling QoE for various types of cloud games in light of different video encoding bitrates and frames per second (fps) [18]. Results confirmed the need to adopt different service adaptation strategies for different categories of games.

The general problem of achieving QoE-driven cloud gaming adaptation has been recently addressed in a number of studies [2], [19]–[24]. Tian *et al* [21] formulate and solve a constrained stochastic optimization problem to minimize overall cost for cloud gaming providers, while adjusting data center selection, virtual machine (VM) allocation, and video bitrate configuration for each user. Achieving cost-effective placement of VMs running cloud gaming servers while maintaining sufficient QoE is further addressed by Hong *et al* [20]. In recent work, Basiri *et al.* [22] present a resource allocation framework for cloud centers, focusing specifically on accurate delay modeling as the main control parameter for QoE.

In addition to consideration of issues such as optimized CPU/GPU allocation and VM placement, an important consideration is optimized codec configuration subject to bandwidth constraints. In this work, we focus on this issue and investigate how optimized video configuration across multiple game flows sharing a common network bottleneck (e.g., sharing the outgoing link of a data center, as portrayed in Figure 1) can maximize QoE and fairness among involved players.

The contributions of this paper are twofold. First, we derive and compare QoE estimation models for three previously tested games (subjective QoE scores reported in [18]). The second contribution is an evaluation of the codec configuration problem under bandwidth constraints, driven by the derived QoE models. Our focus is on investigating how different optimization objectives (in terms of quality and fairness) drive the outcome of adapting multiple simultaneous game flows

[1]https://shield.nvidia.com/support/geforce-now/system-requirements/2

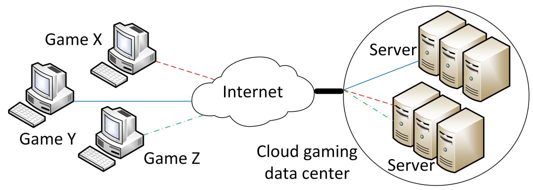


Fig. 1: Cloud gaming service delivered for multiple users over shared bottleneck link

sharing a bottleneck link. We compare different optimization approaches in terms of achievable average MOS, minimum MOS, and fairness.

We note that this problem has been previously tackled by Hong *et al* [2], and we use a similar problem formulation. With respect to [2] we advanced the state of the art by deriving QoE models for a different set of games, where we conducted controlled laboratory subjective studies using the Steam In-home Streaming platform. Additionally, while in [2] the authors address both quality-maximization and quality-fairness objectives, we extend these by incorporating the notion of QoE fairness based on the QoE Fairness Index proposed in [25]. We further extend this investigation by considering the impact of different weight factors assigned to the quality and fairness objectives to show the impact on video bitrate and MOS distributions.

This paper is organized as follows. In section 2 we present our QoE estimation models and compare their performance. In section 3 we present the QoE-aware resource allocation problem for multiple simultaneous users. Further, QoE-aware algorithms used in server-side service adaptation are described. Section 4 reports on numerical results of running the algorithms for different problem instances, while Section 5 provides concluding remarks.

II. QoE MODELS FOR CLOUD GAMING

QoE estimation models, obtained from subjective studies, are needed to perform QoE-aware adaptation of cloud gaming streams to various network and system availability constraints. Obtained models may further be used to drive utility-based network and system resource allocation decisions under limited resource availability. In our previous work [16] we have derived quadratic QoE models for different types of games, namely Serious Sam 3 (SS3) as a representative first person shooter, and Hearthstone (HS) as a representative card game. In a subsequent study using the same methodology and same cloud gaming service, we tested a new game, Orcs Must Die! Unchained (OMD). The QoE study consisted of 28 players (8 novice, 9 intermediate and 11 experienced participants) participating in two and a half hour long gaming sessions that were conducted in a laboratory environment as shown in Figure 2. Valve's Steam In-Home streaming service was used as the supporting platform for cloud gaming[2] and the tested game was played at 720p resolution. The participants were divided in 7 gaming groups with 4 players in each group. Each of the groups played SS3 and OMD approximately for an hour. While playing, the participants could see each other's screens and freely communicate. During the experiments, we manipulated video bitrate and video frame rate as two key video encoding parameters heavily impacting players' QoE. A total of 24 different scenarios were tested by each group. The conducted study and its findings are reported in [18][3], however QoE modeling results have not been previously reported. Therefore, we develop a quadratic QoE estimation model for the newly tested game OMD, and additionally evaluate previously derived QoE models by comparing them to newly derived linear QoE estimation models.

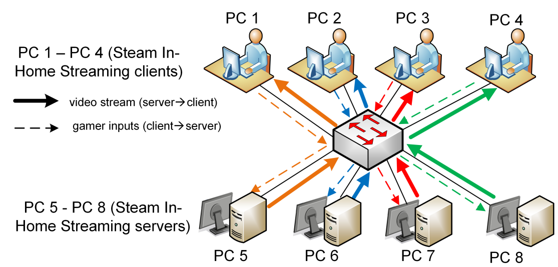


Fig. 2: Experimental setup for the conducted QoE study

In accordance with the controlled parameters in our subjective studies, we model players' QoE as a function of video encoding parameters (frame rate and bitrate) for each of the tested games. Different types of linear and nonlinear models were used to describe the data, and thus obtained models were compared based on their accuracy of fit. A quadratic model, also used in previous research [2], [16], was once again found to give the best results for the given data as compared to other models. The MOS scores were modeled as a quadratic function of video encoding parameters:

$$MOS(g,f,b) = \alpha_{g,1}f + \alpha_{g,2}b + \alpha_{g,3}f^2 + \alpha_{g,4}b^2 + \alpha_{g,5}fb + \alpha_{g,6},$$

where $\alpha_{g,1} - \alpha_{g,6}$ are game specific parameters estimations, b is video game stream bitrate, and f is video frame rate. For comparison purposes, a simpler model was also chosen to describe MOS scores, whereby the QoE scores were modeled as a linear function of video encoding parameters:

$$MOS(g,f,b) = \alpha_{g,1}f + \alpha_{g,2}b + \alpha_{g,3}.$$

Derived QoE models and their parameter estimates are summarized in Table I. As expected, quadratic models achieve much better fit for the collected data compared to linear models for the same game. Given these results, only quadratic models are later used when solving the resource allocation problem in the case of multiple simultaneous players.

Additionally, if we further examine the derived models with regards to achieved best MOS under different bitrate values, we notice similar video quality saturation while increasing video bitrate, as reported also by [2]. However, the observed

[2]Steam In-Home streaming, http://store.steampowered. com/streaming/

[3]Complete results of subjective studies with all user scores are available at www.fer.unizg.hr/qmanic/data_sets.

TABLE I: Derived QoE estimation models for tested games

	Linear model	R^2	Quadratic model	R^2
Serious Sam 3	$-2.396 * 10^{-3} f + 0.127b + 2.77$	0.779	$2.843 * 10^{-2} f + 0.404b + 6.4 * 10^{-5} f^2 - 3.125 * 10^{-2} b^2 + 3.427 * 10^{-3} fb + 2.611$	0.986
Orcs Must Die! Unchained	$4 * 10^{-4} f + 6.595 * 10^{-2} b + 3.397$	0.403	$3.477 * 10^{-2} f + 0.343b - 6.31 * 10^{-4} f^2 - 3.086 * 10^{-2} b^2 + 3.284 * 10^{-3} fb + 2.058$	0.864
Hearthstone	$3.35 * 10^{-4} f + 3.181 * 10^{-2} b + 4.186$	0.481	$3.404 * 10^{-2} f + 6.057 * 10^{-2} b - 4.54 * 10^{-4} f^2 - 4.808 * 10^{-3} b^2 + 8.63 * 10^{-4} fb + 3.473$	0.782

saturation (shown in Figure 3) is manifested in our QoE models at much higher bitrate levels compared to the results reported by the authors in [2]. For SS3, it occurs close to 9.8 Mbps and for OMD near 8.2 Mbps (compared to 2 Mbps for all games reported in [2]), while for HS there is no video quality saturation. Beyond the saturation point (i.e., at higher bitrates) MOS values which models report are replaced with MOS values at the saturation points so as to maintain monotonicity. These findings are taken into account while utilizing QoE models to drive resource allocation decisions, as described later on.

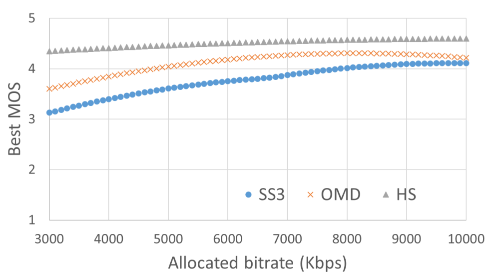


Fig. 3: Video quality saturation for different games

III. QoE-aware resource allocation

To meet end-user QoE requirements, and reduce system and network load, the cloud gaming service needs to dynamically adapt to varying system and network conditions. In commercial implementations, service adaptation is commonly performed on the server-side by changing video encoding configuration parameters (e.g., frame rate, video bitrate, resolution) of a game stream with respect to available network bandwidth (estimated at the client) and number of active players. As mentioned, previous studies have shown that such adaptation strategies should also consider type of played game as a key context parameter [18].

A. QoE-driven adaptation for multiple simultaneous players

Our main objective is to maximize overall players' QoE while making efficient use of available resources. As a result, the aim is to improve QoE for active gaming session players, considering demands and available resources, achieved by adapting video encoding configurations to network constraints. Derived QoE models can be used to estimate MOS for a given combination of video encoding parameters and game type.

The notation used in our problem formulation is given in Table II. We formulate the problem as follows. Each player p from all active players N is assigned to a server in a data center and starts playing game g_p (g_p is one of the available games G). The data center uses an outgoing data link for sending video game streams corresponding to all players, and B represents available link bandwidth. In this case, the bandwidth denotes the available resources for video bitrates, thus ignoring bandwidth usage of higher-layer protocols. We let f_p ($f_{min} \leq f_p \leq f_{max}$) be frame rate and bit_p ($bit_{min} \leq bit_p \leq bit_{max}$) be the bitrate of a game stream for each of the active players. We set the minimum frame rate f_{min} to 25 fps and the maximum frame rate f_{max} to 60 fps, as our proposed QoE models (utilized for estimating the QoE scores) are based on subjective studies where frame rate was varied between these two values. Moreover, the maximum frame rate of 60 fps is a typical frame rate that average experienced players consider sufficient without perceiving quality degradations. Likewise, we set the minimum bitrate bit_{min} to 3 Mbps and the maximum bitrate bit_{max} to 10 Mbps, with the same reasoning used as for frame rate. Additionally, our empirical tests using the Steam-In Home Streaming service have shown that using video bitrates less than 3 Mbps leads to a video with high visual degradations. We note that in [2] the authors consider constraints imposed by each client's access network conditions. For simplification purposes, we do not consider this constraint for now, and assume that each client is capable of streaming up to the bitrate allocated by our resource allocation algorithm. We let m_{g_p,f_p,bit_p} be the MOS score of playing game g_p at frame rate f_p and bitrate bit_p. We use the derived QoE models for estimating the MOS scores based on the video encoding parameters. The decision variables are frame rate f_p and bitrate bit_p for each player, thus solving the problem corresponds to finding players' video encoding configurations that achieve the highest players' QoE in the system with regards to currently available effective bandwidth.

For this problem, we define and compare the following objective functions: (i) maximize average MOS across all players (*max-avg quality* objective); (ii) maximize minimal MOS across all players (*max-min quality* objective); and (iii) maximize a weighted sum of average MOS across all players and fairness (*max-avg quality-fairness* objective). We refer to the QoE fairness index as introduced in [25], [26], and defined as follows: $F = 1 - \frac{2\sigma}{H - L}$, where σ is the standard deviation of QoE scores, L is the lower bound and H is the

TABLE II: Used notation

N	number of players
B	available effective bandwidth
G	available games
g_p	selected game by player p
f_{max}	maximum frame rate (set by administrator)
f_{min}	minimum frame rate (set by administrator)
f_p	target frame rate for player p
bit_{max}	maximum bitrate (set by administrator)
bit_{min}	minimum bitrate (set by administrator)
bit_p	target bitrate for player p
m_{g_p,f_p,bit_p}	the MOS score for game g at frame rate f and bitrate br played by player p

upper bound of the used rating scale. The QoE fairness index as a standalone metric does not rate the level of QoE that the service achieves, but rather quantifies achieved QoE fairness (as opposed to QoS fairness) of the system on a scale of [0;1].

Based on described definitions, we formulate the service adaptation problem as a mathematical problem with the max-avg quality objective function as follows:

$$\max \sum_{p=1}^{N} m_{g_p,f_p,bit_p} \tag{1}$$

$$\text{s.t. } 1 \leq p \leq N \tag{2}$$

$$g_p \in G, \forall p \tag{3}$$

$$bit_{min} \leq bit_p \leq bit_{max}, \forall p \tag{4}$$

$$\sum_{p=1}^{N} bit_p \leq B \tag{5}$$

$$f_{min} \leq f_p \leq f_{max}, \forall p \tag{6}$$

For the max-min quality objective, the objective function Eq. 1 is replaced with $\max \min_{p=1}^{N} m_{g_p,f_p,bit_p}$. In the case of the max-avg quality-fairness objective, the objective function is $\max((1-\theta)\sum_{p=1}^{N} m_{g_p,f_p,bit_p} + \theta F)$, where parameter θ denotes relevance of the fairness in the system. We note that in this case MOS scores are normalized, with 1 indicating highest MOS and 0 indicating lowest MOS.

B. Algorithm description

For solving the optimization problems, we base our approach on the optimal algorithms proposed in [2] that proved to be efficient in solving this problem. The basic idea is to first set each player's bitrate to the lowest possible value, and iteratively allocate small chunks of bandwidth to the player with the largest MOS gain. Thereby, for the *max-avg quality* objective problem, we allocate additional bandwidth (if available) in repeated steps to the players for which a gain of added bitrate results with the highest increase of MOS in the system. Similarly, for the *max-min quality* objective problem, bandwidth is allocated to the player with the lowest MOS score. For the *quality-fairness* objective problem, the algorithm is the same as for its equivalent quality objective problem, however fairness in the system is considered while evaluating players' MOS scores during allocation steps. Lastly, we compare chosen algorithms with a baseline algorithm that allocates the same amount of bandwidth to all active players, irrespective of game type. The baseline algorithm also does not adapt video frame rate, but rather keeps it constantly at approx. 60 fps, as we observed from the default Steam In-Home Streaming resource allocation algorithm. It should be noted that all of these algorithms assume monotonicity of the model functions, i.e., an increase of video bitrate results with a boost in MOS score, which is met by our QoE models after saturation correction, as described in the previous section.

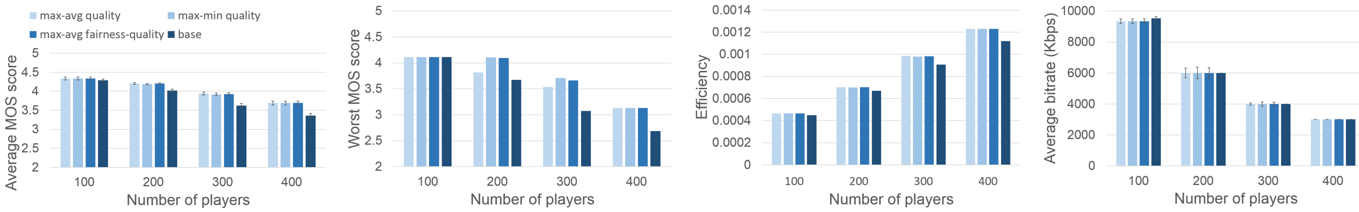
IV. Numerical results

A. Description of the case study

We solve the previously described service adaptation problem by defining instances of the problem with various numbers of simultaneous players $N \in (100, 200, 300, 400)$. In each instance, we assume an equal distribution of players across games (assuming the aforementioned three games presented in Section II). We let the available effective bandwidth be constant through the instances and equal to the amount of bandwidth necessary for providing all players with minimal video bitrate in the instance with the highest number of players. As a result, in the case of 100 players, the service can allocate as much bandwidth as is necessary for each of the players, and with 400 players in the system, each player gets a minimal possible video bitrate (i.e., 3 Mbps). All defined problem instances are solved utilizing each of the resource allocation algorithms, so as to compare their performance. The minimum step for resource allocation in all implemented algorithms is 100 Kbps, which should be more appropriate for real-time service adaptation as compared to smaller allocation steps. For the *max-avg fairness-quality* algorithm, we set parameter θ to 0.5 to make the system relatively fair in terms of achieved MOS for the players. With that in mind, we observe the following metrics: MOS (average and minimum MOS), allocated bitrate per player, and efficiency (defined as ratio between the average MOS and consumed bandwidth in Mbps). Obtained results are reported in the following subsections.

B. Performance evaluation

We first investigate the performance of the algorithms compared to the baseline algorithm. We can observe in Figure 4a that all implemented algorithms achieve higher average MOS compared to the baseline algorithm, and that the difference increases as the number of players grows. Furthermore, it can be noticed that the algorithms that take into account players' QoE during resource allocation obtain similar average MOS at the same interval. However, these algorithms perform differently when observing the lowest MOS in the system, as shown in Figure 4b. The algorithms that emphasize fairness (max-min quality and max-avg fairness-quality algorithms), as expected result in higher minimum MOS values as compared to other algorithms, and consequently less players experiencing poor gaming quality. Therefore, prior to performing resource allocation, a provider should consider different optimization



(a) average MOS scores (b) minimum MOS scores (c) efficiency (d) average allocated bitrate per player

Fig. 4: Performance of the tested algorithms

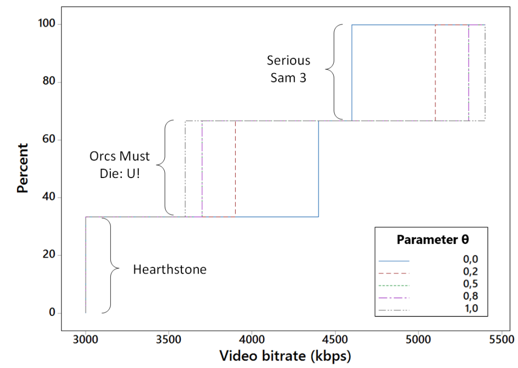
goals and select the most appropriate algorithm depending on their business model. Additionally, while comparing the algorithms that consider fairness in the system, it is visible that the algorithm that incorporates QoE-fairness into a weighted optimization objective function (with equal relevance assigned to fairness and quality) provides similar average and minimum MOS results as the algorithm that maximizes the minimum MOS in the system. In the following section we further explore the impact of varying this relevance factor.

With respect to efficiency of the algorithms (Figure 4c), we observe an increase with a decrease of the bandwidth that can be allocated to the players, and it changes similarly for all implemented QoE-aware algorithms. In the case of bitrate allocation per player, we observe that all algorithms have on average the same amount of bitrate assigned to all players (Figure 4d). For the case with 100 players, as a result of previously mentioned video quality saturation while increasing bitrate, players on average have assigned less than max achievable bitrate, even though additional bandwidth is available.

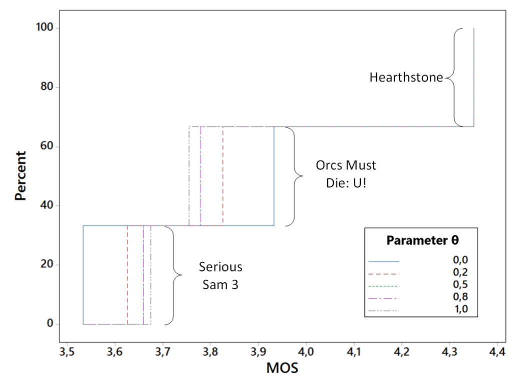
C. The impact of fairness relevance on the resource allocation

We investigate the impact of the parameter θ on average/minimum MOS values and bitrate, thus examining the impact when varying the relevance of fairness as compared to quality maximization in the system. The results have shown that changing the value of the θ parameter has minimal impact on average and minimum MOS scores (this being a result of the QoE models used). However, the parameter adjustment directly impacts the distribution of the allocated bandwidth between players in the system.

We solve the optimization problem with 300 concurrent players while also adjusting θ from 0 (which results in the *max-avg quality* objective) to 1 (objective function maximizes fairness with no relevance assigned to quality maximization). Even though the impact is minimal in terms of average and minimum MOS scores in the system, the bandwidth distribution is significantly altered between the games, as can be observed in Figure 5a, in accordance with the change of MOS scores (Figure 5b). With an increase in θ, more bitrate is allocated to the game with lower gains of MOS per bitrate (SS3) by reducing the bitrate previously allocated to the game with higher gains (OMD). The algorithm attempts to equalize average MOS score of these two games to increase fairness



(a) CDF for video bitrate



(b) CDF for MOS scores

Fig. 5: CDFs for allocated video bitrates and MOS scores in a scenario with 300 users. Different values of θ illustrate the impact of fairness relevance.

in the system, as there is no available bandwidth to increase MOS scores for both games. Meanwhile, the bitrate for HS gaming sessions always stays at the lowest values (as HS has significantly higher QoE scores at lowest level compared to QoE scores at highest level for other two games), even in the case when fairness is not considered. Even though the QoE-aware algorithms have assigned minimal video bitrate for HS sessions, the players' QoE is not degraded. However, by doing so, more bitrate can now be allocated to other gaming sessions, thus illustrating the benefit in cases when server-side service adaptation algorithms consider game QoE models (either per-game or per-game category).

V. Conclusions

In this paper we have built upon previous studies and presented an optimization problem for QoE-aware resource allocation for cloud gaming. The aim is to allocate bitrate across multiple simultaneous players in the system (potentially playing different types of games) so that the players achieve highest QoE under given bandwidth availability constraints. From a service provider perspective, this amounts to configuring video encoding parameters (bitrate, frame rate) of cloud gaming sessions in a QoE-aware manner. Therefore, we model a player's QoE for a given game as a function of video encoding parameters, with subjective studies confirming that different models are needed for different game types. Obtained models are subsequently utilized by QoE-aware algorithms for driving resource allocation decisions.

We compare the outcome of four different algorithms, by solving the optimization problem for different numbers of simultaneous players. The results have shown that QoE-aware algorithms achieve higher average MOS scores compared to a baseline algorithm. Furthermore, we compare two different algorithms that consider QoE-fairness, and show that they achieve similar average and minimum MOS scores under tested conditions, albeit exhibiting different bitrate distributions. We go beyond state-of-the-art by studying the impact of considering QoE fairness in the optimization objective (as opposed to QoS fairness captured by the baseline algorithm). By varying the relevance of QoE fairness in the objective, we see a significant impact on the actual bitrates (optimal resource allocation) allocated across different game sessions. Hence, we conclude that by optimizing a weighted multi-objective function, service providers are able to tune to what extent QoE fairness should be considered.

While reported findings are based on the utilized QoE models, conclusions regarding the need to consider fairness and the impact this decision has on the resource allocation can be generalized. Ongoing work is addressing QoE modeling for a wider scope of game types, and further utilization of these models in system and resource allocation problems. We aim to extend work to also jointly considering optimized resource allocation in both the cloud gaming data center and across relevant network links.

VI. Acknowledgements

This work has been supported in part by the Croatian Science Foundation, project UIP-2014-09-5605 (Q-MANIC).

References

[1] M. Suznjevic, I. Slivar, and L. Skorin-Kapov, "Analysis and QoE evaluation of cloud gaming service adaptation under different network conditions: The case of NVIDIA GeForce NOW," in *8th Intl. Conf. on Quality Of Multimedia Experience (QoMEX)*. IEEE, 2016, pp. 1–6.

[2] H.-J. Hong, C.-F. Hsu, T.-H. Tsai, C.-Y. Huang, K.-T. Chen, and C.-H. Hsu, "Enabling Adaptive Cloud Gaming in an Open-Source Cloud Gaming Platform," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. PP, no. 99, pp. 1–14, 2015.

[3] Z. Li, H. Melvin, R. Bruzgiene, P. Pocta, L. Skorin-Kapov, and A. Zgank, *Lag Compensation for First-Person Shooter Games in Cloud Gaming*. Cham: Springer International Publishing, 2018, pp. 104–127.

[4] S. Schmidt, S. Zadtootaghaj, and S. Mller, "Towards the delay sensitivity of games: There is more than genres," in *Proc. of 9th QoMEX*, May 2017, pp. 1–6.

[5] M. Claypool and D. Finkel, "The effects of latency on player performance in cloud-based games," in *Proc. of 13th NetGames*, 2014, pp. 1–6.

[6] I. Slivar, M. Suznjevic, and L. Skorin-Kapov, "Empirical QoE Study of In-Home Streaming of Online Games," in *Proc. of the 14th Annual Ws on Net. and Sys. Support for Games, NetGames*, Nagoya, Japan, 2014.

[7] Z.-Y. Wen and H.-F. Hsiao, "QoE-driven performance analysis of cloud gaming services," in *16th Intl. Ws. on Multimedia Signal Processing (MMSP)*. IEEE, 2014, pp. 1–6.

[8] Y. Liu, S. Wang, and S. Dey, "Content-aware modeling and enhancing user experience in cloud mobile rendering and streaming." *IEEE J. Emerg. Sel. Topics Circuits Syst.*, vol. 4, no. 1, pp. 43–56, 2014.

[9] M. Jarschel, D. Schlosser, S. Scheuring, and T. Hoßfeld, "Gaming in the clouds: QoE and the users' perspective," *Mathematical and Computer Modelling*, vol. 57, no. 11, pp. 2883–2894, 2013.

[10] P. Quax, A. Beznosyk, W. Vanmontfort, R. Marx, and W. Lamotte, "An evaluation of the impact of game genre on user experience in cloud gaming," in *Games Innov. Conf. (IGIC), IEEE Intl.*, 2013, pp. 216–221.

[11] V. Clincy and B. Wilgor, "Subjective Evaluation of Latency and Packet Loss in a Cloud-Based Game," in *10th Intl. Conf. on Information Technology: New Generations (ITNG)*. IEEE, 2013, pp. 473–476.

[12] S. Möller, D. Pommer, J. Beyer, and J. Rake-Revelant, "Factors influencing gaming QoE: Lessons learned from the evaluation of cloud gaming services," in *Proceedings of the 4th International Workshop on Perceptual Quality of Systems (PQS 2013)*, 2013, pp. 1–5.

[13] Y.-T. Lee, K.-T. Chen, H.-I. Su, and C.-L. Lei, "Are all games equally cloud-gaming-friendly? An electromyographic approach," in *11th Ws on Net. and Sys. Support for Games, NetGames*, 2012, pp. 1–6.

[14] S. Wang and S. Dey, "Modeling and characterizing user experience in a cloud server based mobile gaming approach," in *Global Telecommunications Conference, GLOBECOM*. IEEE, 2009, pp. 1–7.

[15] I. Slivar, M. Suznjevic, and L. Skorin-Kapov, "The impact of video encoding parameters and game type on QoE for cloud gaming: A case study using the Steam platform," in *7th Intl. Ws on Quality of Multimedia Experience (QoMEX)*, May 2015, pp. 1–6.

[16] I. Slivar, L. Skorin-Kapov, and M. Suznjevic, "Cloud gaming QoE models for deriving video encoding adaptation strategies," in *Proceedings of the 7th Intl. Conf. on Multimedia Systems*. ACM, 2016, p. 18.

[17] S. Zadtootaghaj, S. Schmidt, and S. Möller, "Modeling gaming qoe: Towards the impact of frame rate and bit rate on cloud gaming," in *10th Intl. Conf. on Quality of Multimedia Experience (QoMEX)*, 2018.

[18] I. Slivar, M. Suznjevic, and L. Skorin-Kapov, "Game Categorization for Deriving QoE-Driven Video Encoding Configuration Strategies for Cloud Gaming," *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, vol. 14, no. 3s, p. 56, 2018.

[19] D. Wu, Z. Xue, and J. He, "iCloudAccess: Cost-Effective Streaming of Video Games From the Cloud With Low Latency," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 24, no. 8, pp. 1405–1416, Aug 2014.

[20] H. Hong, D. Chen, C. Huang, K. Chen, and C. Hsu, "Placing virtual machines to optimize cloud gaming experience," *IEEE Transactions on Cloud Computing*, vol. 3, no. 1, pp. 42–53, Jan 2015.

[21] H. Tian, D. Wu, J. He, Y. Xu, and M. Chen, "On achieving cost-effective adaptive cloud gaming in geo-distributed data centers," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 25, no. 12, pp. 2064–2077, Dec 2015.

[22] M. Basiri and A. Rasoolzadegan, "Delay-aware resource provisioning for cost-efficient cloud gaming," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 28, no. 4, pp. 972–983, April 2018.

[23] M. Amiri, A. Sobhani, H. A. Osman, and S. Shirmohammadi, "Sdn-enabled game-aware routing for cloud gaming datacenter network," *IEEE Access*, vol. 5, pp. 18 633–18 645, 2017.

[24] Y. Deng, Y. Li, R. Seet, X. Tang, and W. Cai, "The server allocation problem for session-based multiplayer cloud gaming," *IEEE Transactions on Multimedia*, vol. 20, no. 5, pp. 1233–1245, May 2018.

[25] T. Hoßfeld, L. Skorin-Kapov, P. E. Heegaard, and M. Varela, "Definition of qoe fairness in shared systems," *IEEE Communications Letters*, vol. 21, no. 1, pp. 184–187, 2017.

[26] T. Hoßfeld, P. E. Heegaard, L. Skorin-Kapov, and M. Varela, "No silver bullet: QoE metrics, QoE fairness, and user diversity in the context of QoE management," in *9th Intl. Conf. on QoMEX*. IEEE, 2017, pp. 1–6.