QoE-Analysis of 5G Network Resource Allocation Schemes for Competitive Multi-User Video Streaming Applications

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***Abstract*—Competitive demand for network resources has only increased during the emergence of 5G next generation cellular technology. As video streaming accounts for an overwhelming percentage of this demand, the importance of considering the often-neglected Quality of Experience (QoE) metric is essential to ensure network resources are allocated in the most effective manner. Generalized network throughput metrics are insufficient in capturing the full human experience as increased data rates do not necessarily translate to improvements in user utility. Our study compares the efficacy of existing network allocation algorithms and proposes new approaches to 5G network resource allocation schemes using a more inclusive snapshot of user demand. We provide recommendations on which approach provides the highest QoE performance and suggestions for future network-side improvements. We further propose a QoE-driven network resource allocation (QENA) algorithm that shows a 20% improvement in overall average QoE across a large set of heterogeneous users.**

***Index Terms*—5G, resource allocation, video streaming, network scheduling.**

I. Introduction

Mobile video streaming through applications such as YouTube, Netflix, Hulu, and Amazon Prime has increased greatly over the past decade, while video streaming as a whole is expected to generate over 82% of total cellular traffic past 2022 [1]. Consequentially, the resource demands on cellular networks from users streaming video data far outweighs the demands in e-mails and browsing.

Many 5G network scheduling and resource allocation algorithms proposed in recent years focus primarily on users' received throughput rate. Both an emphasis on overall throughput [2], [3] and consistency [4] have been explored. Consideration of queue size when prioritizing demand has further improved user satisfaction over a given time horizon. Yet many approaches fail to mitigate penalties for users with poor channel conditions.

Most of these attempts limit their scope of evaluation to a single quantifiable variable. Prior research [5] has shown the importance of considering the full Quality of Experience (QoE) as a qualitative expression of the network resources received by each individual user. Limiting our understanding of a highly variable human experience with a purely quantitative approach restricts our capacity to reallocate resources for an overall improved utility experience.

In this paper, we first compare the efficacy of existing classes of network resource allocation algorithms in achieving high QoE values. We then seek to consider the full "snapshot" of each individual user in our proposed resource allocation algorithms in order to balance overall network throughput with aggregate QoE metrics. To elaborate, we consider current channel conditions, prior allocated resources, existing buffer status, and remaining video download length in our inputs.

Our results show the effectiveness of our algorithm in managing the tradeoffs between overall throughput and QoE over realistic wireless networks in which users have varying channel quality and experience competition for network resources. We compare our algorithm with existing allocation schemes to show significantly higher QoE when modeling real wireless traces.

Our contributions are as follows. First, we establish the motivation behind QoE metrics. Second, we categorize and define a large spread of resource allocation schemes into four specific classes. Next, we adapt these methods for implementation in video streaming on mobile devices using 5G cellular networks. Finally, compare overall QoE performance of existing algorithms and establish the effectiveness of an improved algorithmic approach.

The remainder of this paper is organized as follows. In Section II we introduce the video streaming model, the background behind QoE, and the user download policy. Foundations for understanding different network resource allocation policies are provided. Section III is comprised of simulation parameters for the subsequent results comparing QoE performance across various network resource allocation algorithms. We provide a discussion of related work in Section IV along with conclusions in Section V.

II. Problem Formulation

A. Video Streaming

We consider a system in which users stream videos stored on a remote server over shared wireless links. The users buffer a portion of the video before starting playout. The client may provide a very large buffer that can store the entire video, in which case the video may be downloaded as fast as the network and server can support while the user is playing the video out on their device. One drawback with this approach

TABLE I: Summary of Methods for Network Resource Allocation, Type 1

Algorithm Class	**Generalized Objective**	**Algorithm 1 parameter $\xi_{\mathbf{u}}(\mathbf{t})$**
Opportunistic	$u^*(t) = \arg\max_{u\in U} R_u(t)$	$\theta_u(t)$
Back Pressure	$u^*(t) = \arg\max_{u\in U} R_u(t)Q_u(t)$	$\theta_u(t) \cdot \left(\frac{1}{\rho_{ui}(t)}\right)$

TABLE II: Summary of Methods for Network Resource Allocation, Type 2

Algorithm Class	**Allocated Resource Blocks**	**Algorithm Implementation**
Consistent Rate	$B_u(t) = \Psi^{max}/R_u(t)$ for $u \in U$	Algorithm 2
Equal Share	$B_u(t) = M/N$ for $u \in U$	Algorithm 3
QENA	$B_u(t) = M \cdot \left(\frac{q_{ui}(t)/\rho_{ui}(t)}{\sum_v q_{vi}(t)/\rho_{vi}(t)}\right)$ for $u \in U$	Algorithm 3

is that a user may not watch the entire video in which case the resources used to download the video, including device energy and network capacity, are wasted. Therefore in our system clients buffer a portion of the video for playout, and fetch further segments to buffer as the playout is progressing.

The clients run the DASH-inspired online bitrate selection algorithm (OBA) that attempts to maximize their QoE [5]. QoE is a function of the resolution of the video playout, how often and by how much the resolution changes, and how many re-buffering events take place. For a high QoE it is best to play out high resolution videos with no outages or transitions to lower resolutions. However, this is not always possible when considering network conditions or energy constraints of mobile devices. Lower resolution video frames require less data transfer and can therefore be transferred in less time; this may be necessary if network rates are low or connectivity is intermittent and the video buffer on a client is emptying. Receiving video at a lower rate and rendering lower resolution videos on a mobile device may also be required to save device energy.

In our system the video server has a file reserve with a set of resolutions for each video segment, typically ranging between 144p and 1080p or above for mobile devices. The resolution of the video downloaded to the users is governed by what the algorithm requests and what the network can deliver. A user will request a resolution based on the size of their screen and the energy they wish to expend on downloading and playing the video. This requested resolution may be adjusted by the client depending on the status of the playout buffer and the available transfer rates from the network.

Our work seeks to provide comparison of network-side resource allocation policies for 5G video streaming applications and demonstrate which approach provides the best overall QoE across users.

B. *QoE Expression*

QoE is quantified using a 5-level rating scale, and model values are taken from experimental data [5], [6]. We use the standard QoE formulation as follows[1]:

$$QoE = \sum_{u,i} \left(\Omega_{ui} - I_{ui}^{tran}\right) \tag{1}$$

where $\quad I_{ui}^{tran} = f_{ui}^{rebuff} \cdot I^{rebuff} + f_{ui}^{bitrate} \cdot I^{bitrate},$

and Ω_{uj} being the $MOS5$ mean opinion score corresponding to the resolution selected by user u to download segment i, and I_{ui}^{tran} is the $MOS5$ impact from data transmission preventing the user from experiencing the full QoE value. Specifically, the transmission impact I_{ui}^{tran} is a function of the frequency of rebuffering and bitrate decrease for each downloaded segment, and their respective impacts. Prior research [7] has determined that a 3.0 Mbps decrease in resolution has the same impact on a viewer's quality as 1 s of rebuffering. Hence, we set $I_{ui}^{rebuff} = I_{ui}^{bitrate}$ and scale the bitrate "frequency" changes $f_{ui}^{bitrate}$ by 3 Mbps. Full expressions include $f_{ui}^{rebuff} = \frac{(\tau_{ui}-\rho_{ui})_+}{\rho_{ui}}$ and $f_{ui}^{bitrate} = \frac{\left(v_{u(i-1)}-v_{ui}\right)_+}{3.0\text{ Mbps}}$. Observe τ_{ui} is the

[1]The impact of vibration, I_{ui}^{vib}, has been removed from the QoE equation to restrict the scope of evaluation.

time required by user u to download[2] semgnet i, v_{ui} is the corresponding selected bitrate and ρ_{ui} is the buffer state at the beginning of download segment i. Note that I^{rebuff} = $I^{bitrate}$ = 0.742 have been empirically set from prior work [7] [9]. We provide a list of relevant parameters and their associated definitions in Table III.

Intuitively, we observe that the quantitative expression for QoE is a function of (a) the given video resolution, (b) rebuffering penalties and (c) resolution decrease penalties.

C. User Rate Request

OBR, a recently developed algorithm for context-aware and energy-aware video streaming on smartphones, provides a QoE-focused approach to a DASH-inspired video segment download policy [5]. The algorithm outputs a desired bitrate resolution at which to download subsequent video segments associated with a requested rate from the network. The OBR algorithm provides improved performance beyond the current YouTube algorithm and closely approaches optimal selection. Equivalent energy consumption parameters for 5G implementation are taken from existing experimental data [10].

D. Network Resource Allocation

We define 5G network resource allocation as the division of a set number of physical resource blocks (PRB) amongst requesting users. Consider the throughput rate $\Theta_u(t)$ for user u at time t denoted by

$$\Theta_u(t) = R_u(t) \cdot B_u(t)$$

given the per-resource-block-rate $R_u(t)$ and the network allocated resource blocks $B_u(t)$ to individual u at time t.

For all algorithms, we first assume all users receive their requested rate if there are sufficient resources to meet the user requests. In cases in which not all user requests can be fulfilled, the algorithms activate to assign resources. The following classes are demonstrative of a spread of various network resource allocation algorithms. A summary of network resource allocation classes is provided in Tables I and II.

1) Algorithm Classes, Type 1: Opportunistic and Back Pressure inspired algorithms are classified as Type 1 and summarized in Table I. Type 1 algorithms are considered *ranked user* algorithms, meaning they allocate the full requested rate to users who are prioritized by the algorithm. One downside to Type 1 algorithms is that low-priority users are completely neglected. Algorithm 1 encompasses the resource allocation policy for both the generalized Opportunistic and Back Pressure algorithms.

Opportunistic: The Opportunistic algorithm class seeks to maximize the total sum of rates experienced by all individual users [2], [3] and is associated with *MaxRate* policies. The algorithm solely intakes a user's requested rate and estimated

[2]We assume τ_{ui} includes promotion, concurrent playout, and rebuffering periods [8].

TABLE III: Algorithm Parameters

Variable	Definition
U	Set of active streaming users inside a given cell
Ω_{uj}	Mean QoE opinion score at bitrate selected by user u for segment i assuming full segment playout
I^{tran}_{uij}	Transmission impact on QoE for user u during download of segment i given resolution j
f^{rebuff}_{uij}	Frequency of rebuffering given u, i, j
I^{rebuff}	Rebuffering impact on QoE
$f^{bitrate}_{uij}$	Frequency of bitrate changes given u, i, j
$I^{bitrate}$	Bitrate impact on QoE
$R_u(t)$	Throughput received by user u at time t
$Q_u(t)$	Queue size of user u at time t
Ψ_{max}	Maximum achievable consistent rate [4]
v_{uij}	Bitrate selected by user u for segment i download given resolution index j
ρ_{ui}	Buffer status of user u at the beginning of downloading segment i
τ_{ui}	Total time required by user u to download segment i
N	Total number users requesting network resources
M	Resource blocks in a given network cell
$B_u(t)$	Resource blocks allocated to user u at time t
$\theta_u(t)$	Per-resource-block-rate achievable by user u at time t
r_{ui}	Throughput rate requested from the network by user u while downloading segment i
q_{ui}	Remaining video needing to be downloaded by user u while downloading segment i, in seconds

channel conditions while ignoring the full user context, such as relevant buffer status and remaining download queue As a result, users may be starved of resources as a penalty for poor channel conditions.

Back Pressure: Also referenced as the *MaxWeight* policy [2], [11], [12], the Back Pressure approach has the benefit of prioritizing resources towards low-buffer or high-queue individuals. Users are ranked in allocation order by their queue size demand scaled by their current estimated channel conditions. Downsides from this method primarily emerge from continuing to penalize users with poor channel conditions.

2) Algorithm Classes, Type 2: Consistent Rate, Equal Share based, and QENA algorithms are classified as Type 2 and summarized in Table II. Type 2 algorithms are *fractional sharing* algorithms, meaning that all users are allocated resource blocks proportional to a given criteria. While no user is neglected, some users may receive fewer resources than requested. Algorithm 2 is associated with the Consistent Rate formulation and Algorithm 3 denotes the allocation policy for both Equal Share and the proposed QENA algorithms.

Consistent Rate: In an attempt to provide mobile device users with a consistent rate using 5G network allocation parameters, prior work by Mehmeti has derived the maximum achievable consistent rate Ψ_{max} for such scenarios [4]. This maximum rate Ψ_{max} is a function of the overall user outage probability meaning, as a result, many network resources become underutilized in highly volatile network conditions.

Equal Share: Inspired by Round Robin scheduling policies [13], [14], the desire to allocate the same number of resource blocks to each user provides a fairness benefit as the achieved rate is directly propositional to each individual's per-block-rate [8].

Proposed QENA Algorithm [8]: The objective for Quality of Experience Driven Network Resource Allocation (QENA) involves allocating resource blocks inversely proportional to the length of each user's current buffer status. The QENA algorithm seeks to balance prioritization of low-buffer individuals without egregious poor channel condition penalization. While back pressure grants the full requested rate to users with low-buffer priority, QENA will sacrifice some of the requested resource blocks in order to ensure users with poor channel conditions are not fully neglected.

Algorithm 1 Resource Allocation Algorithm: $\xi_u(t)$

for $t = 1, \ldots, T,$ **do**

Rank users according to the $\xi_u(t)$ parameter value given in Table I.

Allocate the number of resource blocks required to achieve the requested throughput rate, starting at the highest $\xi_u(t)$ and in descending order.

Stop allocation once resource blocks are no longer available.

end

Algorithm 2 Consistency Algorithm

for $t = 1, \ldots, T,$ **do**

Calculate $X_n(t, \Psi^{max}) = \sum_u \frac{\Psi^{max}}{MR_u(t)}$.

if $X_n(t, \Psi^{max}) \leq 1$ **then**

Allocate resource blocks to each active user as $\frac{\Psi^{max}}{R_u(t)}$ for $u \in U$.

else

Distribute resource blocks equally across all actively requesting users.

end

end

Algorithm 3 Generalized Resource Allocation

for $t = 1, \ldots, T,$ **do**

if $\sum_u \frac{r_u(t)}{\theta_u(t)} > M$ **then**

Allocate resource blocks to each active user using the expression for $B_u(t)$ given in Table II corresponding to the desired allocation method.

else

Allocate the number of resource blocks required to achieve the requested throughput rate as $B_u(t) = \frac{r_u(t)}{\theta_u(t)}$.

end

end

III. RESULTS

In this section we outline the simulation parameters and discuss the associated QoE results for the various network resource allocation classes.

A. Simulation Parameters

We set 21 users per cell, 7 with "good" channel conditions, 7 with "moderate" channel conditions, and and 7 with "poor" channel conditions. We assume a 5G network channel bandwidth of 100 MHz (frequency range 410 MHz - 7125 MHz) available for video streaming, equivalent to 273 physical resource blocks (PRB) with a subcarrier spacing (SCS) of 30 kHz [15]. We consider a range of channel conditions ranging from 0.45 Mbps/block to 8 Mbps/block. We choose the standard 15 CQI index levels for 5G and arbitrarily set a CQI of 1 as a per-resource-block-rate of 0.45 Mbps/block and a CQI of 15 as an 8 Mbps/block for simplicity. While these

TABLE IV: Method comparison with average values across five iterations for a single cell of ten users with an hour long video stream

Resource Allocation Method	Channel Conditions	Normalized User QoE	Segments With Resolution Decreases	Segments With Rebuffering	Resource Starved Users
Opportunistic	Good Users	0.966	9.0%	1.9%	1.7%
	Moderate Users	0.910	17.1%	5.7%	2.3%
	Poor Users	0.738	14.3%	2.4%	2.5%
	AVERAGE	0.871	13.5%	3.3%	2.1%
Back Pressure	Good Users	1.000	11.4%	2.9%	2.5%
	Moderate Users	0.909	18.1%	5.7%	2.7%
	Poor Users	0.738	14.3%	2.4%	3.0%
	AVERAGE	0.883	14.6%	3.7%	2.7%
Consistent Rate	Good Users	0.796	4.8%	0.5%	0.0%
	Moderate Users	0.781	8.1%	2.4%	0.0%
	Poor Users	0.612	8.6%	1.9%	0.0%
	AVERAGE	0.729	7.1%	1.6%	0.0%
Equal Share	Good Users	0.961	10.5%	2.9%	0.0%
	Moderate Users	0.857	15.7%	3.8%	0.0%
	Poor Users	0.778	11.9%	2.4%	0.0%
	AVERAGE	0.865	12.7%	3.0%	0.0%
QENA	Good Users	0.995	9.0%	1.4%	0.0%
	Moderate Users	0.937	17.1%	3.8%	0.0%
	Poor Users	0.775	11.4%	1.0%	0.0%
	AVERAGE	0.903	12.5%	2.1%	0.0%

values would be dependent on the proprietary mapping of any specific service provider, they are merely representative of a range of conditions users might experience in 5G.

We define "high" channel quality as CQIs ranging uniformly between 8 through 15 (explicitly, 2.5 - 8 Mbps/block), with our simulation average of 5 Mbps/block. "Low" channel quality encompasses CQIs between 1 through 8 (0.45 - 2.5 Mbps/block), averaging around 1.21 Mbps/block. Block-rate conditions are set to fluctuate on the order of 100 ms. The exchange between good and bad states is modeled using a two-state Markov chain.

Primarily "good" users have a probability of remaining in the high state as $q_{high} = 140/141$, with an expected residency time of 14 s, and a probability of remaining in a low state as q_{low} = 60/61, with an expected residency time of 6 s. Similarly, "poor" users have a probability of remaining in the high state as q_{high} = 60/61, with an expected residency time of 6 s, and a probability of remaining in a low state as q_{low} = 140/141, with an expected residency time of 14 s.

"Moderate" users fluctuate between "high" and "low" channel conditions, each with an expected residency time of 10 s where q_{high} = q_{low} = 100/101. Reported RSRP values range from -140 dBm to -44 dBm. While not directly correlated, we set the signal strength for users with CQI of 1 to RSRP = -120 dBm and users with CQI of 15 to RSRP = -50 dBm for simplicity. The remaining RSRP values are obtained by interpolating between these two anchors.

B. Algorithm Performance

In this section, we provide a critical analysis of the QoE performance results encapsulated in Table IV. We provide average value comparisons across five iterations for a single cell of twenty-one users with a simulated hour-long video stream. Users request sequential two-second video clip segments from the video server individually at one of six resolution options (144p, 240p, 360p, 480p, 720p, or 1080p). The average user QoE output is normalized to the method user subset with the highest quality rating. The segments with resolution decreases and segments with rebufferings are reported as a percentage of the affected video segments over the total number of downloaded segments. Starved users are represented by the average percentage of users who are denied any resource blocks, whether during playout or rebuffering.

Opportunistic: While seeking to be throughput optimal, the opportunistic inspired resource allocation approach experiences QoE disadvantages stemming from a lack of resources allocated to poor network channel condition users in the face of competition. While good and moderate users are consistently provided for, poor users have some of the highest rates of resolution decreases and rebuffering due to a lack of allocated resource blocks. All users, regardless of good, moderate, or poor channel conditions, are prone to neglect and experience resource starvation.

Back Pressure: While the back pressure inspired algorithm outperforms opportunistic allocation as expected, the high level of rebufferings and resolution fluctuations provide severe penalties to this approach. While back pressure is successful at targeting low-buffer individuals in need of network resources, the over-zealous approach tends to penalize higher-buffer individuals over time. Scaling this effect might reduce these penalties, but would require an unrealistic future knowledge of channel conditions to perfectly optimize the expression. While good channel condition users have the highest overall average QoE, the back pressure inspired algorithm sacrifices overall quality through QoE penalties from rebuffering and resolution decreases. This approach further exhibits the highest rates of resource starvation.

Consistent Rate: The consistent rate allocation scheme under-performs as a consequence of the under-utilization of network resources for the sake of throughput stability [4]. However, this method provides the lowest average numbers of resolution fluctuations and rebufferings, which for specific users may be much preferred to experiencing the video stream at unnecessarily high resolutions given the accompanying volatility. In this method, no user is completely neglected in the division of network resources.

Equal Share: The more straightforward of the resource allocation algorithms, this equal share inspired approach to network resource allocation is surprisingly effective in comparison. Equal share provides the benefit of ensuring all users have a nonzero resource block allocation with the individual's channel conditions accounting for the differences in experienced utility. The user subset QoE ratings are relatively proportional to aggregate channel conditions, despite moderate users experiencing the higher QoE penalties.

Proposed QENA Algorithm: Providing the best of both worlds, the proposed QENA algorithm successfully ensures no user is neglected in the division of physical resource blocks across users. Furthermore, the higher video resolutions received are not as severely penalized by the given rebufferings and resolution fluctuations. Moderate users are the most successful across the given methods and low-end users are not egregiously penalized or starved for their poor channel conditions.

C. Discussion

Opportunistic, Back Pressure and Equal Share provide a provide a similar average QoE; however, each is accompanied by a set of tradeoffs. Both Opportunistic and Back Pressure have the largest percentage of resource starved users at 2.1% and 2.7% respectively. Furthermore, Back Pressure has the highest percentage of segments with resolution decreases at 14.6%. While QENA does not provide the highest QoE for primarily "good" channel condition users (0.961), the benefits averaged across a large range of channel conditions, given a noramlized user QoE of 0.903, is higher than Back Pressure, with a normalized user QoE of 0.883, despite Back Pressure outperforming for primarily "good" users (1.000). Consistent Rate has the lowest percentage of resolution decreases (7.1%) and rebufferings (1.6%), yet downloads video segments systematically at lower resolutions than the other four methods providing the lowest normalized user QoE at 0.729. In comparing these five network resource allocation methods, these results demonstrate that QENA provides the best mitigation of QoE-related tradeoffs.

IV. Related Work

The quantitative expression for quality of experience (QoE) in video streaming is a function of (a) the given video resolution, (b) rebuffering penalties and (c) resolution decrease penalties [8], [5], [6], [7], [9]. Existing network resource allocation classes ignore one or more of these essential components.

Surveys on network resource allocation for both 5G and LTE [13], [2] discuss opportunistic, back pressure, consistent-rate, fairness-based, and round robin algorithm classes. Opportunistic [2], [3], equal share [13], [14], and consistency [4] algorithms provide adequate performance while policies incorporating queue or buffer state, such as back pressure [2], [11], [12], are often more effective at meeting long-term user demand for service satisfaction. However, note that opportunistic and back pressure algorithms are faulty in that users with poor channel conditions are still penalized and therefore frequently starved for resources. Consistent rate algorithms often leave network resources underutilized. Equal share approaches further lack the adaptability required the long term QoE benefits.

In this paper, we introduce the QENA algorithm where the throughput rate is a function of channel conditions and buffer status for video streaming applications.

V. Conclusion

Various network resource allocation schemes are evaluated and discussed in the context of overall user QoE for video streaming scenarios. Our results show the effectiveness of our QENA algorithm in managing the tradeoffs between overall throughput and QoE over realistic wireless networks in which users have varying channel quality and experience competition for network resources. Our contribution with the QENA network resource allocation algorithm provide alternatives which address all three necessary components of the standard QoE metric.

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