




# Ensuring the QoE-related Fairness to Reduce the User Abandonment Ratio

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**Abstract:** These days, it is quite a challenge for app owners to keep users engaged with an app. Currently, the level of user abandonment is one of the key parameters that application owners are interested in. To meet these challenges, we are conducting an extended study of a previously proposed solution that significantly reduces the abandonment rate of a given application. The investigated solution is based on the methods of fairness using QoE and QoS approach. This paper shows that application abandonment ratios can be reduced by using an appropriate approach to fair bandwidth allocation. Adjusting the bandwidth allocation to users taking into account the quality of the user experience has a more effective effect on reducing app abandonment ratios than if quality of service is taken into account. This is because the users make the decision to abandon the application based on their feelings rather than technical parameters. In order to effectively reduce application abandonment ratios, a suitable bandwidth allocation algorithm must be used. This paper presents the impact of using different algorithms on the abandonment ratio and compares the popularly used algorithms and the previously proposed bandwidth allocation algorithm.

**Keywords:** fairness; QoE; QoS; abandonment ratio

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## 1. Introduction

In recent years, network traffic has increased significantly, which is a direct cause of resource allocation problems. One of the primary resources that require thoughtful allocation is bandwidth. Furthermore, network traffic is expected to continue to grow in the next years, so, the problem of fair network bandwidth allocation and the associated abandonment of applications by users will continue to be an important issue.

In the past, quality of service (QoS) parameters such as packet loss, latency, jitter and bandwidth were used to measure user satisfaction from service or application. However, when there are currently so many different devices and applications in a network requiring completely different technical parameters, such measurement is not unambiguous and therefore insufficient. Therefore, a need has emerged for another way of measuring the user satisfaction with the service based more on the subjective opinion of users or on the user's experience of using the service (often referred to as the quality of experience – QoE [1]). Such a measurement characterises the user's level of satisfaction with a given application or service, taking into account technical parameters and personality or the current user impressions. It is an essential factor because based on the user's satisfaction, the user decides to abandon or stay with a given application/service [2]. Paper [3] compares the impact of interference, its intensity and temporal dynamics, on user engagement in the context of video streaming. However, it did not propose ways to increase engagement or reduce abandonment.

As shown in [4], [5], one of the main factors influencing the abandonment ratio is a long application loading time. From this, it can be deduced that the number of abandonments is directly influenced by bandwidth distribution among the end-users.

39 In this paper, we would like to answer the question: will a corresponding change in  
 40 the used fairness approach originally based on QoS parameters towards the one based on  
 41 QoE the number of application abandonments by users? To the best of our knowledge,  
 42 this question has not been answered in the related literature yet.

### 43 1.1. Fairness Algorithms based on QoS Parameters

44 There are certain algorithms used to ensure fairness. The most popular one is  
 45 max-min algorithm [6]. It starts with zero resource allocation for all nodes and next tries  
 46 to increase the assignment of the network link resources to users until the link becomes  
 47 saturated. The result of the max-min algorithm is, therefore, a full allocation of the  
 48 resource such that users with fewer resources have obtained the requested capacity [6,7].

49 Another important algorithm is the proportional fairness algorithm [7]. In this case,  
 50 the user is allocated a resource proportional to the request made.

### 51 1.2. Measurement of QoS Fairness

52 The most popular measure of fairness is the one proposed by Jain in [8]. The highest  
 53 value of fairness based on this measure occurs when all users get the same equal resource  
 54 allocation, or some users get no allocation, while the rest get an equal share of resources.  
 55 In the case of not getting any resources, the situation is manifestly and intuitively unfair.  
 56 However, the case of equal resource allocation does not translate to an equal range  
 57 of user experience because each user has different hardware, which translates into a  
 58 different quality [9]. Furthermore, the work [10] very bluntly dismisses equal flow as  
 59 a solution that is unfair. Since the user decides whether to abandon the application  
 60 based on feelings and subjective measures rather than objective technical parameters, an  
 61 equal distribution of service quality parameters will not be beneficial to the providers of  
 62 applications.

### 63 1.3. QoE Algorithm

64 To provide certain minimum values of QoE parameters, specific standards have  
 65 been created. One of the most commonly used standards for delivering video services is  
 66 DASH (Dynamic Adaptive Streaming over HTTP). It is based on dividing content into  
 67 a sequence of small files based on the HTTP protocol. Each of these files represents a  
 68 short fragment of the transmission of playback content, no more than a few seconds.  
 69 These segments can be transmitted at different bit rates and are then concatenated into a  
 70 single coherent content. The intention is to minimise the number of content playback  
 71 interruptions that may occur due to the changing network conditions [11]. The DASH  
 72 standard is intended to assure high utilisation of network resources and provide stable  
 73 quality of service and increase the user sense of QoE, which is extremely important to  
 74 reduce the risk of application and service abandonment.

75 One approach to optimising the network resource allocation and quality adaptation  
 76 that fairly maximises the QoE of users is shown in [12]. However, in that paper, the  
 77 authors focus only on one type of service, i.e., video spinning.

### 78 1.4. Measure of QoE Fairness

79 Concerning QoE-related fairness, the measured subjective perceptions of end-users  
 80 must be equal for all. One of few coefficients to measure fairness precisely in the context  
 81 of QoE is the index proposed in [13] and developed in [14].

$$F = 1 - \frac{2\sigma}{H - L} \quad (1)$$

where:

$$\sigma^2 = \frac{1}{n-1} \sum_{i=1}^n (Y_i - \mu)^2 \quad (2)$$



$$\mu = \frac{\sum_{i=1}^n Y_i}{n} \quad (3)$$

82 where:

83  $i$  is the user index,

84  $Y_i$  is parameter of QoE,

85  $L$  is the lowest bound of QoE parameter,

86  $H$  is the upper bound of QoE parameter,

87  $n$  is standard deviation of QoE parameter,

88  $\mu$  is arithmetic mean of QoE parameter.

89

90 The main difficulty in using this measure is the effective and appropriate mapping  
91 of the technical parameters of the network – QoS to the quality of experience parameters  
92 of users – QoE [15].

93 MOS – Mean Opinion Score

94 The mean opinion score is the most commonly used measure to determine the  
95 quality of the experience. It is used to express the quality of a system. It is most often  
96 calculated as an arithmetic mean of the collected user opinions. However, this method  
97 is time-consuming and expensive. This is due to the need to involve many people to  
98 express their opinion. Objective quality methods are also used. These methods are  
99 trained based on the use of opinions set by people [16].

100 In this paper, a 5-degree scale (1-5) is used (see Table 1), as recommended in [17].

**Table 1.** Five-grade MOS scale from [18].

Opinion	Label
5	Excellent
4	Good
3	Satisfactory
2	Poor
1	Bad

101 The remainder of the paper is organized as follows: Section 2 on motivation for  
102 addressing the topic outlines why we feel there is a need to address the topic of equity  
103 in order to reduce application abandonment. In Section 3, we present the necessary  
104 formulas describing the relationship between QoS and QoE parameters for selected types  
105 of applications. In Section 4, we present our algorithm from [19], here accompanied  
106 with an extended set of possible scenarios to be investigated, while in Section 5, we  
107 provide description of the respective simulation assumptions. The results of comparison  
108 of the investigated algorithm with commonly used methods are presented in Section 6.  
109 Section 7 concludes the paper.

## 110 2. Motivation for Addressing the Topic

111 Providers and users evaluate the performance of the application. Providers mostly  
112 often use quality-of-service parameters such as throughput, latency, or loss ratio. How-  
113 ever, users are less interested in technical parameters and primarily base their opinions  
114 on subjective perceptions, i.e., quality of experience (QoE). Users expect good perceptual  
115 quality, which can be derived from many factors, including not only technical parameters  
116 but also user experience [2].

117 Current solutions available for fair resource sharing primarily focus on allocating  
118 capacity based on QoS parameters only. However, such an approach does not provide  
119 adequate QoE values. A strategy that focuses on considering fairness from the QoE

120 perspective guarantees higher overall end-user satisfaction and thus reduces the number  
121 of users abandoning the applications.

122 We present our solution to address the lack of appropriate mechanisms to ensure  
123 QoE fairness for different types of applications. In our solution, we divide users into  
124 satisfied and unsatisfied users and ensure equal QoE performance among satisfied users,  
125 regardless of the application used.

126 This algorithm mainly targets large subnetworks where users are aware of other  
127 users' experience, including, e.g., online game championships, where users are aware  
128 of the feelings of other players, or large subnetworks such as corporations, student  
129 residences or university campuses. In such sub-networks, users of different types  
130 of applications co-exist, are in direct contact with other users, and are aware of the  
131 experience of other users' application usage.

132 In our previous paper [19], we proposed a fairness algorithm designed for a limited  
133 set of application types. In the current paper, the implementation of the algorithm has  
134 been extended to cover a broad range of application types and different arrival times of  
135 requests.

### 136 3. Expected User Opinion

137 In this paper, we refer to four types of different applications: file downloading, web  
138 browsing, VoIP according to G.722 codec and VoIP according to G.726/G.727 codec. The  
139 opinion is expressed on a 5-degree MOS scale. We define an unsatisfied user as a user  
140 whose quality of experience is low enough to abandon the used application. An opinion  
141 equal to 3.0 was arbitrarily chosen as the boundary between the groups of satisfied  
142 and unsatisfied users. When the user's opinion is below 3.0 – the user is referred to as  
143 unsatisfied (and satisfied, otherwise).

#### 144 3.1. Web Browsing

145 According to the research results described in [20], the relationship between long  
146 session duration and end-user feedback can be expressed as follows:

$$MOS_i = 5.72 - 0.936 * \log(session\_time_i) \quad (4)$$

147 where  $i$  is the user number,  $session\_time$  is the duration of the user's web browsing in  
148 seconds.

#### 149 3.2. File Downloading

150 In the case of file downloading, one of the most important parameters for the user's  
151 perception of the quality of experience is bandwidth. Another essential parameter is the  
152 file size which affects the user's expected download time.

153 In [21], the Formula 5 was provided to represent the user's opinion depending on  
154 the file size and bandwidth:

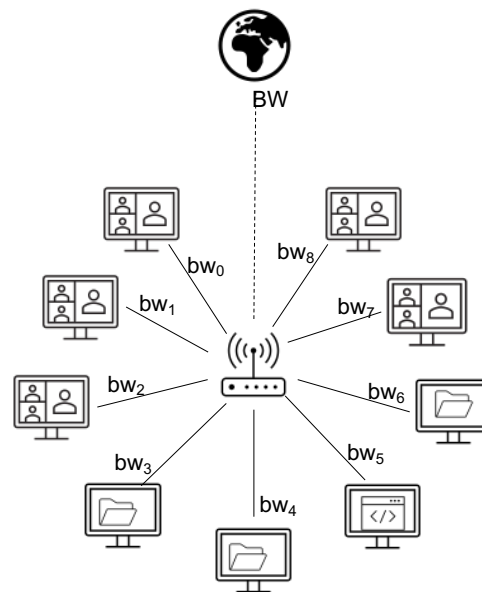
$$MOS_i = \frac{0.755}{\sqrt{f_i}} * \log(bw_i) + 1.268 \quad (5)$$

155 where  $i$  this is the user's number,  $f$  is the normalized download size in bits,  $bw_i$  is the  
156 allocated bandwidth in bps.

#### 157 3.3. VoIP

Paper [22] presents the results of a study on the effect of allocated bandwidth on  
the user opinion for VoIP applications. The respective VoIP-related measure from [22] is  
presented in Formula 6.

$$MOS_i = a - b * \ln\left(\frac{c}{bw - d}\right) \quad (6)$$



**Figure 1.** The topology used in this paper for investigation of the fairness schemes.

158 where  $i$  this is the user's number,  $bw$  denotes allocated bandwidth in bps while  $a$ ,  $b$ ,  
 159  $c$  and  $d$  are generic parameters depending on the codecs used (as paper [22] does not  
 160 detail the meaning of the individual parameters  $a$ ,  $b$ ,  $c$  and  $d$ ).

#### 161 4. Methods

##### 162 4.1. Investigated Algorithm

163 The goal of the algorithm is to distribute bandwidth fairly in terms of QoE for  
 164 satisfied users and fairly in terms of QoS for unsatisfied users. Our algorithm is based  
 165 on dividing users into satisfied and unsatisfied based on the predicted final user opinion.  
 166 The final opinion is predicted based on the developed patterns tailored to the type of  
 167 application used by the user. As an input, the user provides the desired bandwidth size,  
 168 the type of application being used and the parameters needed to support the application.  
 169 In the case of downloading files it is the size of the file, in the case of web surfing it is the  
 170 size of the web page, in the case of VoIP services it is the duration of the service.

171 We use a star topology in this paper. In Fig. 1,  $bw_i$  refers to the maximum bandwidth  
 172 of user  $i$ . While  $BW$  refers to the outgoing link capacity. The entire algorithm is presented  
 173 in Fig. 2.

##### 174 4.2. Consecutive Steps of Our Algorithm

175 *Users Send Requests:* The user sends a request to the computing unit. The request contains  
 176 information such as the maximum possible bandwidth for a given user, type of served  
 177 application and other parameters such as the size of the downloaded file (in the case of  
 178 file downloading) or the size of the webpage (in the case of web browsing).

179  
 180 *Calculation of Initial Users' Subjective Opinions:* The computing unit calculates the prelimi-  
 181 nary values of the subjective opinion of the users based on the considered applications.

182  
 183 *Division of Users Into Groups of Satisfied and Unsatisfied Users:* Based on opinions calculated  
 184 in the previous stage, users are divided into those who are satisfied and those who are  
 185 unsatisfied.

186

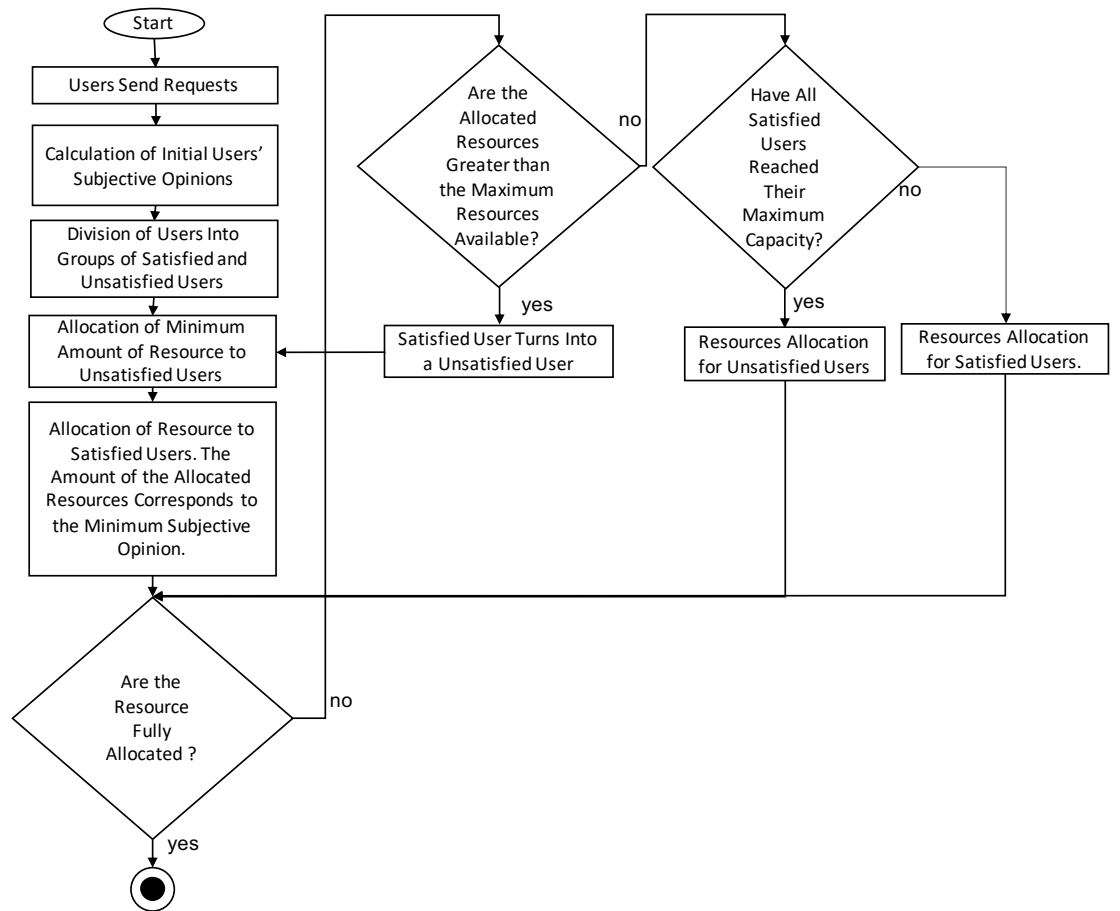


Figure 2. Scheme of the Algorithm.

*Allocation of Minimal Amount of Resources to Unsatisfied Users:* Unsatisfied users are allocated a minimum bandwidth, following the approach from [19], as defined by Formula 7:

$$bwTemp_l = q \cdot bwTemp_{minUnsatisfied} \quad (7)$$

187 where:

188  $l$  – index of the unsatisfied user ( $l = 1, 2, 3, \dots, k$ ),

189  $q$  – service provider's coefficient  $q \in (0, 1 >$ ,

190  $bwTemp_{minUnsatisfied} = \min(bw_{min}; \frac{BW}{n})$ ,

191  $bw_{min}$  – minimum request bandwidth among unsatisfied users.

192

193 *Allocation of Resources to Satisfied Users. The Amount of the Allocated Resources Corresponds to the Minimum Subjective Opinion.:* The bandwidth is allocated to all satisfied users according to the formula in accordance with using application (Formula 4, 5 or 6).

196

197 *Are the Resources Fully Allocated?:* This step is to verify whether the amount of allocated resources for satisfied and unsatisfied users sums up to the maximum available amount.

199 *Are the Allocated Resources Greater than the Maximum Resource Available?:* The purpose of this step is to verify if the amount of allocated resources for satisfied and unsatisfied users is greater than the maximum amount of available resources.

202 *Satisfied User Turns Into an Unsatisfied User:* If the amount of allocated resources for satisfied and unsatisfied users is greater than the total amount of available resources, it is necessary to move one user who is satisfied to unsatisfied to release the allocated bandwidth. In order to release as much of the resources as possible at the lowest possible cost concerning the increase of the number of unsatisfied users, it is necessary to apply this change to the user who requires the largest amount of resources.

208

209 *Have All Satisfied Users Reached Their Maximum Capacity?:* This step is to check if all satisfied users have reached their maximum capacity.

211

212 *Resource Allocation for Satisfied Users:* If not all satisfied users have reached maximum bandwidth, bandwidth is allocated to satisfied users with minimum subjective opinion increase.

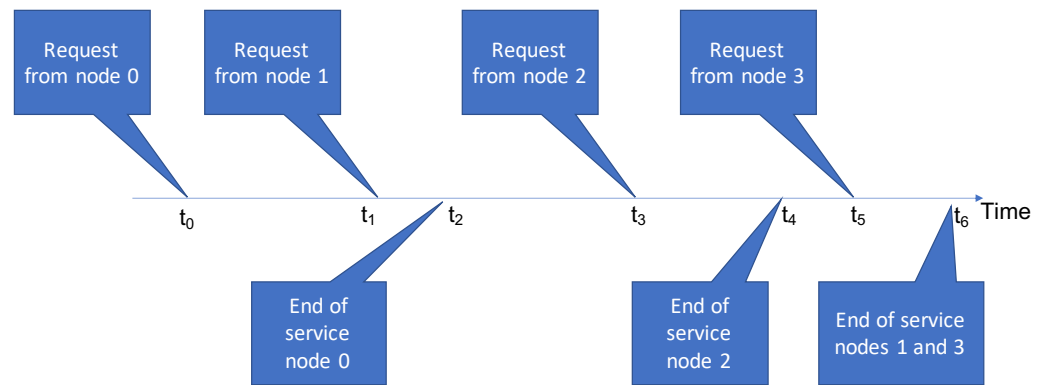
215

216 *Resource Allocation for Unsatisfied Users:* Suppose the bandwidth is distributed according to all the previous steps and the amount of bandwidth allocated to all users is less than the total available outgoing link capacity, and all satisfied users have reached their maximum bandwidth. In that case, the remaining part of the bandwidth is distributed among unsatisfied users. It is worth noting that this operation will not change the status of unsatisfied users to satisfied users but is intended to maximize the usage of the entire network resources.

### 223 4.3. Example of Use Case the Investigated Algorithm

224 An example of using the algorithm is shown in Fig. 3. At time  $t_0$  user  $n_0$  makes  
225 a request to utilize a given application. At time  $t_0$ , the bandwidth allocated to that  
226 application is calculated according to the investigated algorithm. Then, at time  $t_1$ ,  
227 another request comes – this time from user  $n_1$ . Again, the bandwidth allocation for  
228 users  $n_0$  and  $n_1$  is calculated. At time  $t_2$ , user  $n_0$  stops using the application and, once  
229 again, the bandwidth allocation is re-calculated for the user who continues to use the  
230 application.





**Figure 3.** Example of use case the investigated algorithm.

### 231 5. Algorithm Assumptions

232 As mentioned in Section 3.1, in this paper we focus on four types of applications:  
 233 file downloading, web browsing, VoIP according to G.722 codec, and VoIP according to  
 234 G.726/G.727 codec. Limiting MOS value classifying users into satisfied and unsatisfied  
 235 is arbitrarily set to 3.0. Simulations were carried out for a outgoing link capacity equal to  
 236 500 Mbps and for different numbers of users. The number of users was ranged between  
 237 10 and 750. Only in the case of the analysis for application distribution scenario 3 (see  
 238 Table 3), where users are only using a web surfing, the outgoing link capacity was  
 239 10Mbps. This is due to the fact that application distribution scenario 3 is not very  
 240 demanding in terms of desired bandwidths and has a short execution time. To model  
 241 the network congestion scenario, we reduced the outgoing link capacity to 10 Mbps.

242 In order to use formula (6), it was necessary to determine values of parameters  $a$ ,  
 243  $b$ ,  $c$  and  $d$ . This is because when trying to reproduce the graph from the paper [22], it  
 244 was noticed that after substituting given parameter values, it was not possible to obtain  
 245 the same graph. However, in order not to abandon the data presented in the paper,  
 246 the measurement points presented in the graphs were used in [22]. Based on these  
 247 points, coefficients matching Formula (6) were selected as presented in Table 2 to obtain  
 248 a function similar to that presented in [22].

**Table 2.** Fitting parameters of the general formula based on values from [22] for some codecs.

Codecs	a	b	c	d
G.726 and G.727	1.3557	0.8952	0.7795	13.8186
G.722	1.8778	0.6207	0.2216	4.3825

### 249 6. Results

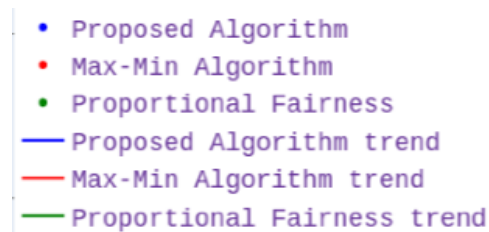
250 Simulations were performed to analyse the number of unsatisfied users after ap-  
 251 plying three bandwidth allocation algorithms: the max-min algorithm, the proportional  
 252 fairness scheme, and our algorithm. Compared to the two common algorithms, the  
 253 number of unsatisfied users was less or equal in all the analysed cases after applying the  
 254 investigated algorithm.

255 All considered scenarios are presented in Table 3. The greatest advantage of the  
 256 investigated algorithm was seen in scenarios of high network congestion. In general, as  
 257 shown later in this paper, as the network load increases, the benefits of the investigated  
 258 algorithm increase as well.

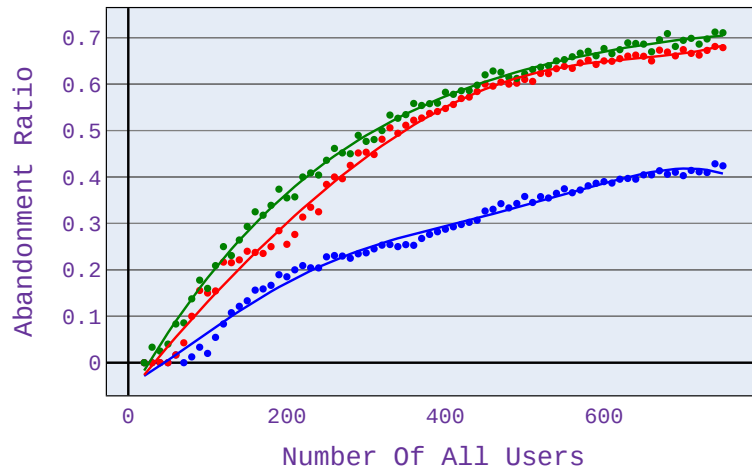


**Table 3.** Analyzed scenarios of distribution of users referring to the considered applications [%].

Application Distribution Scenario	File Downloading	Web Surfing	VoIP codecs G.726 and G.727	VoIP codecs G.722
1	25	25	25	25
2	100	0	0	0
3	0	100	0	0
4	0	0	100	0
5	0	0	0	100
6	50	50	0	0
7	50	0	50	0
8	50	0	0	50
9	0	50	50	0
10	0	50	0	50
11	0	0	50	50
12	0	33	33	33
13	33	0	33	33
14	33	33	0	33
15	33	33	33	0
16	25	75	0	0
17	75	25	0	0
18	25	0	75	0
19	75	0	25	0
20	25	0	0	75
21	75	0	0	25
22	0	25	75	0
23	0	75	25	0
24	0	25	0	75
25	0	75	0	25
26	0	0	25	75
27	0	0	75	25

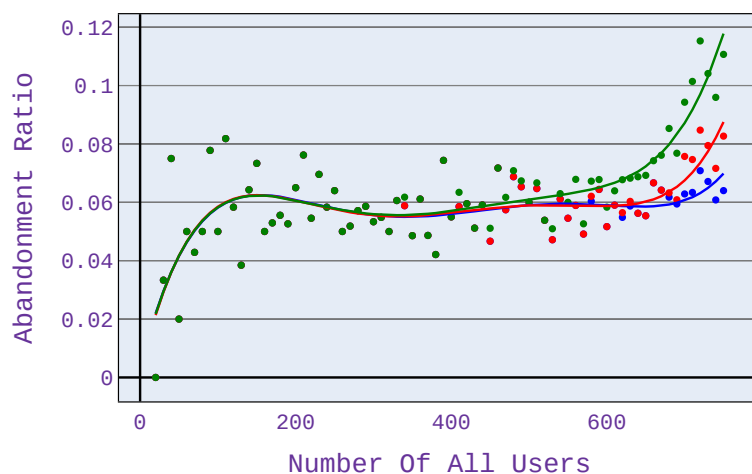
**Figure 4.** The legend valid for all figures in the remaining part of the paper.

## 259 6.1. Relationship Between the Number of Users and Application Abandonment Ratio



**Figure 5.** Abandonment ratio related to the number of users for application distribution scenario 1.

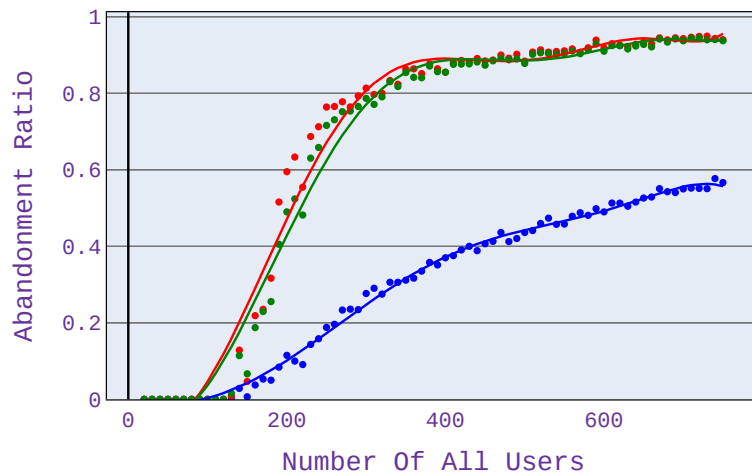
260 When users use different types of applications – as presented in Fig. 5 (25% of users  
 261 download files, 25% of users surf the web, 25% use VoIP services following G.726 or  
 262 G.727 codecs, and 25% use VoIP services following G.722 codecs), the benefits of the  
 263 algorithm become visible already for 50 users. Also, as the number of users increases  
 264 (and thus the size of the network load, too), these benefits increase. At about 400  
 265 users, our algorithm's advantage in terms of reducing the number of unsatisfied users  
 266 (compared to conventional schemes) reaches about 25%. It persists up to the maximum  
 267 load calculated in this simulation.



**Figure 6.** Abandonment ratio related to the number of users for application distribution scenario 2.

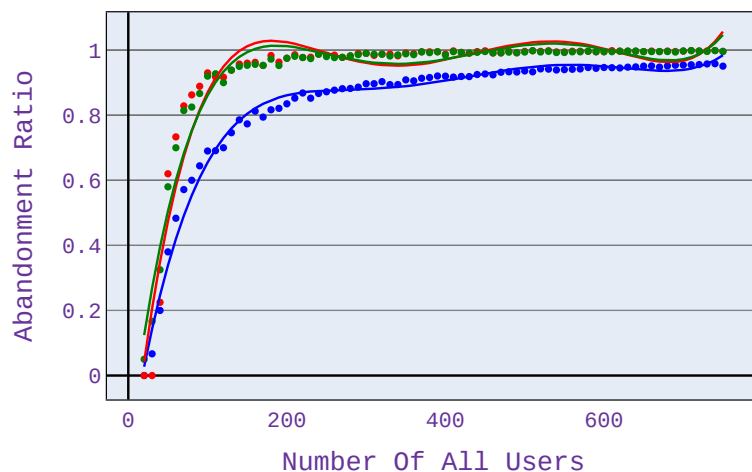
268 In the case scenario 2 – Fig. 6, when users only download files, the benefits are  
 269 visible at high network load – there are at least 700 users served. This is because with  
 270 fewer users, network congestion does not occur, so mechanisms to limit the allocated

271 bandwidth are not triggered. This is because with fewer users, network congestion  
 272 does not occur, so mechanisms to limit the allocated bandwidth are not triggered. It  
 273 is important to note that the different types of applications shown in Figure 6-9 have  
 274 different points of network congestion, and therefore a different trigger point for the  
 275 mechanism responsible for limited bandwidth allocation to users.

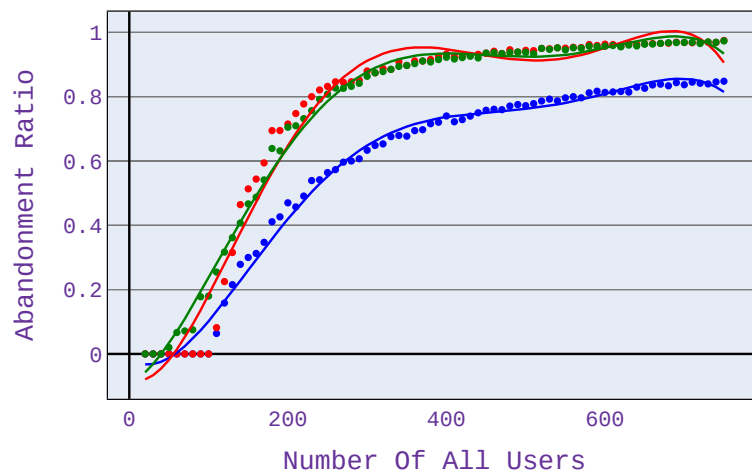


**Figure 7.** Abandonment ratio related to the number of users for application distribution scenario 3.

276 Significant benefits from using our approach can be seen when users only browse  
 277 the web (see Fig. 7). The profit, in this case, reaches up to almost 60% (for 300 users).  
 278 Application providers based on web browsing can benefit the most from the investigated  
 279 algorithm because here the benefits of the investigated algorithm are the greatest ones.



**Figure 8.** Abandonment ratio related to the number of users for application distribution scenario 4.



**Figure 9.** Abandonment ratio related to the number of users for application distribution scenario 5.

280 In Figs 8 and 9, it can be seen that the magnitude of the benefit of the investigated  
 281 algorithm depends on the codecs used when using a VoIP service. For G.726/G.727  
 282 codecs, the benefits are less than for G.722 codecs.

283 For the computations presented in this paper, we use the max-min and proportional  
 284 fairness algorithms based on the most commonly used method, which is the partitioning  
 285 with regard to bandwidth. However, for the algorithm under study, the allocation is  
 286 based on the predicted MOS opinion. This approach helps us to immediately select users  
 287 who will not be satisfied and thus not invest in them and be able to focus our attention  
 288 on users who are potentially satisfied. In the case of algorithms such as max-min or  
 289 proportional fairness which are based only on bandwidth, they are not able to determine  
 290 the users who are worth dropping and thus assign them a higher value of bandwidth  
 291 that they could assign to other users who might be satisfied with this additional value  
 292 of bandwidth. Therefore, the results concerning the number of satisfied users obtained  
 293 by our approach are visibly better than the respective ones for the reference max-min  
 294 scheme (see , e.g., Fig. 7 presenting the advantage of up to 60%).

295 This approach is thus beneficial from the viewpoint of service providers and appli-  
 296 cation owners who compete for every user and who have no advantage in investing in  
 297 users who abandon their application/service.

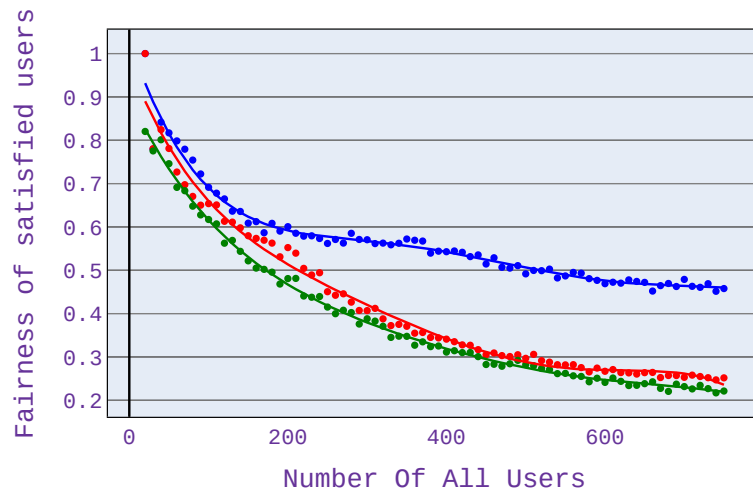
### 298 6.2. Relationship Between the Number of Users and Fairness of Satisfied Users

299 In order to compare fairness values, we also present the user satisfaction factor of  
 300 the fairness measure – this is because comparing only fairness values does not show the  
 301 clear benefit of the investigated algorithm. The strength of the investigated algorithm  
 302 is precisely to minimize the abandonment rate and thus to maximize the number of  
 303 satisfied users. Therefore, it was decided to modify the fairness measure, as presented in  
 304 Formula 8.

$$F_{satisfied} = F_H * m/n \quad (8)$$

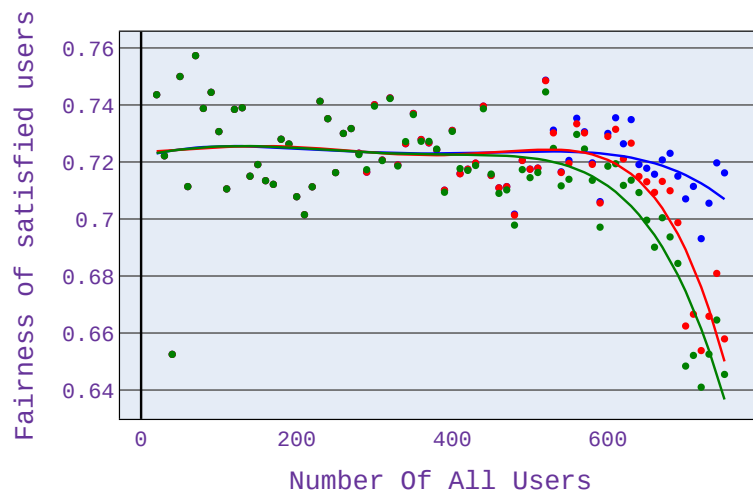
305 where:  $F_H$  – fairness index based on [13],  $m$  – number of satisfied users,  $n$  – number  
 306 of all users.





**Figure 10.** Fairness index for application distribution scenario 1.

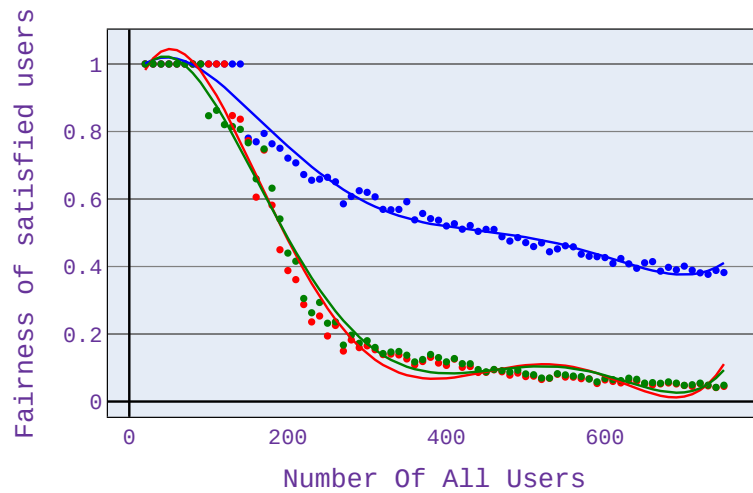
307 As can be seen in Fig. 10, the highest value of the fairness index is achieved for  
 308 application distribution scenario 1 – which means an equal share of different application  
 309 types in the simulation. It is because for this scenario, there is the most significant  
 310 difference in terms of the number of satisfied users among the algorithms used.



**Figure 11.** Fairness index for application distribution scenario 2.

311 As with the abandonment rate analysis for Scenario 2 shown in Fig. 11, higher  
 312 fairness index values occur with more users. As before, this is due to the occurrence of a  
 313 network congestion point.





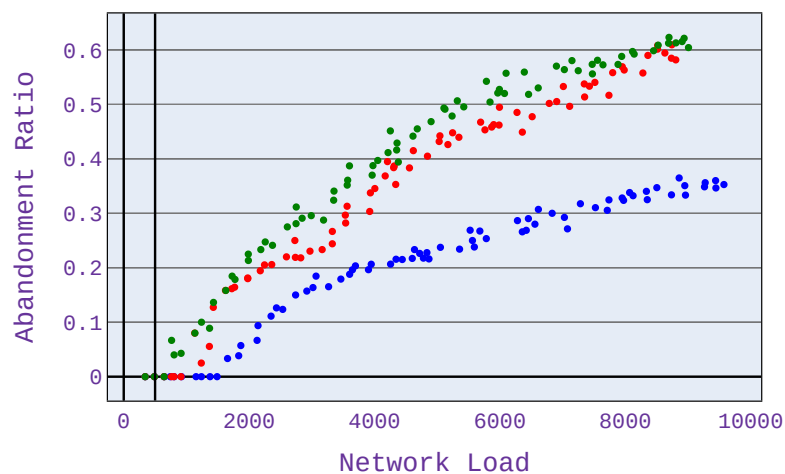
**Figure 12.** Fairness index for application distribution scenario 3.

314 A significant difference in the fairness index can also be seen when using only web  
 315 browsing (Fig. 12). The fairness is then higher even by 40%.

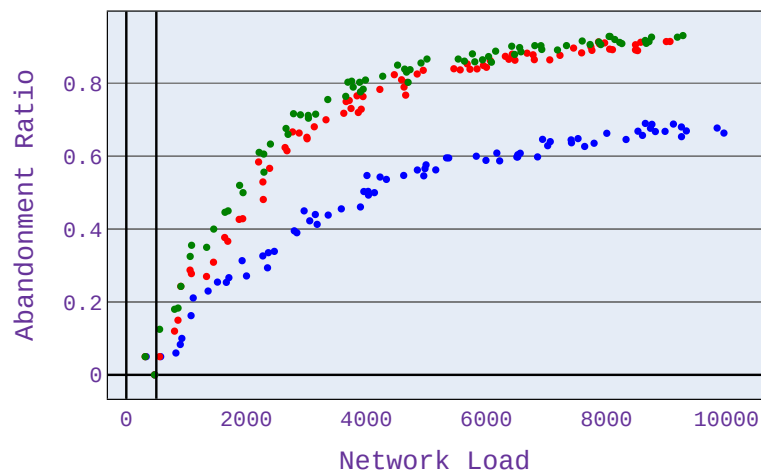
316 Our experiments have also shown that when using only VoIP applications, the  
 317 differences are not so remarkable, although there is a visible gain.

### 318 6.3. Impact of the Chosen Level of Minimum MOS

319 The minimum MOS value, which represents the boundary between satisfied and  
 320 unsatisfied users, has been set to 3.0 in all simulations. However, this is a value that can  
 321 be adjusted as needed. In the following section we show how the abandonment rate  
 322 behaves depending on the set minimum MOS.



**Figure 13.** Abandonment ratio related to mean network load [Mbps] for application distribution scenario 1. Minimum MOS set to 2.0.



**Figure 14.** Abandonment ratio related to mean network load [Mbps] for application distribution scenario 1. Minimum MOS set to 4.0.

323 It can be seen in the pair of Figs 13 and 14, that for a lower value of MOS the  
 324 abandonment ratio is lower. This is due to the lower expectations of users regarding the  
 325 bandwidth allocated allowing to serve more users at a level that satisfies them. However,  
 326 controlling the MOS value should be based on actual data from users. For this purpose,  
 327 it is necessary to collect information from users at what level of satisfaction on a 5-degree  
 328 scale they are satisfied with for a given application. The algorithm can be adjusted so  
 329 that for each application distribution scenario the minimum MOS value is configured at  
 330 a different level.

### 331 7. Conclusion

332 As presented in this paper, the use of equity mechanisms based on the quality  
 333 of experience has a positive effect on reducing abandonment ratios which are often  
 334 high for QoS-related mechanisms. In each of the examples provided, after applying  
 335 the investigated algorithm, the abandonment ratio was lower or equal after applying  
 336 popular algorithms. It is highly beneficial for application providers interested in the  
 337 lowest abandonment ratio and the highest number of users utilizing the applications.  
 338 It is especially noticeable in the case of scenarios 1 and 3 where the differences in the  
 339 size of the abandonment rate between the applied algorithms are the most significant.  
 340 It should be noted that the most significant benefit of the investigated algorithm is in  
 341 situations of high network congestion.

342 The main difficulty in applying our algorithm is the need to determine the QoS-to-  
 343 QoE mapping function. Due to difficulties in performing such a study, there are only a  
 344 few mapping functions available for different types of applications. It, in turn, limits the  
 345 applicability of our algorithm only to applications for which such a function has been  
 346 determined.

347 As future work, a comprehensive study on the mapping of QoS parameters to QoE  
 348 is planned for different types of applications. Ideally, this research should be carried out  
 349 for a significant number of users drawn from different groups to obtain adequate results  
 350 for all users, not just for a particular group.

### References

1. Brunnström, K.; Beker, S.A.; De Moor, K.; Dooms, A.; Egger, S.; Garcia, M.N.; Hossfeld, T.; Jumisko-Pyykkö, S.; Keimel, C.; Larabi, M.C.; others. Qualinet white paper on definitions of quality of experience 2013.



2. Recommendation ITU-T P.10/G.100 – Vocabulary for performance, quality of service and quality of experience. Technical report, 2017.
3. Plakia, M.; Tzamosis, E.; Asvestopoulou, T.; Pantermakis, G.; Filippakis, N.; Schulzrinne, H.; Kane-Esrig, Y.; Papadopouli, M. Should I Stay or Should I Go: Analysis of the Impact of Application QoS on User Engagement in YouTube **2020**. 5. doi:10.1145/3377873.
4. Mobile application abandonment: common reasons. <https://raygun.com/blog/mobile-application-abandonment/>. Accessed: 2020-08-12.
5. The need for mobile speed. <https://www.blog.google/products/admanager/the-need-for-mobile-speed/>. Accessed: 2020-08-12.
6. Nace, D.; Pioro, M. A tutorial on max-min fairness and its applications to routing, load-balancing and network design **2006**.
7. Le Boudec, J.Y. Rate adaptation, Congestion Control and Fairness: A Tutorial **2002**.
8. Jain, R.; Chiu, D.M.; W.R., H. A Quantitative Measure Of Fairness And Discrimination For Resource Allocation In Shared Computer Systems. *CoRR* **1998**, *cs.NI/9809099*.
9. Mansy, A.; Fayed, M.; Ammar, M. Network-layer fairness for adaptive video streams **2015**. pp. 1–9.
10. Briscoe, B. Flow Rate Fairness: Dismantling a Religion. *SIGCOMM Comput. Commun. Rev.* **2007**, *37*, 63–74. doi:10.1145/1232919.1232926.
11. Spiteri, K.; Sitaraman, R.; Sparacio, D. From Theory to Practice: Improving Bitrate Adaptation in the DASH Reference Player **2018**. p. 123–137.
12. Joseph, V.; de Veciana, G. NOVA: QoE-driven optimization of DASH-based video delivery in networks **2014**. pp. 82–90. doi:10.1109/INFOCOM.2014.6847927.
13. Hoßfeld, T.; Skorin-Kapov, L.; Heegaard, P.E.; Varela, M. Definition of QoE Fairness in Shared Systems. *IEEE Communications Letters* **2017**, *21*, 184–187. doi:10.1109/LCOMM.2016.2616342.
14. Hossfeld, T.; Skorin-Kapov, L.; Heegaard, P.; Varela, M. A new QoE fairness index for QoE management. *Quality and User Experience* **2018**, *3*. doi:10.1007/s41233-018-0017-x.
15. Hossfeld, T.; Heegaard, P.; Varela, M.; Skorin-Kapov, L.; Fiedler, M. From QoS Distributions to QoE Distributions: a System’s Perspective **2020**.
16. Shahid, M.; Rossholm, A.; Lövsström, B.; Zepernick, H. No-reference image and video quality assessment: a classification and review of recent approaches. *EURASIP Journal on Image and Video Processing* **2014**, *2014*, 1–32.
17. Recommendation ITU-T P.800.1 –Mean opinion score (MOS) terminology. Technical report, 2016.
18. ITU-T: Recommendation P.800 – Methods for subjective determination of transmission quality. Technical report, 1996.
19. Mazur, I.; Rak, J.; Nowicki, K. Minimising the Churn Out of the Service by Using a Fairness Mechanism **2020**. pp. 117–137. doi:10.1007/978-3-030-50719-0\_10.
20. ITU-T: Recommendation G.1030 – Estimating end-to-end performance in IP networks for data applications. Technical report, 2014.
21. Reichl, P.; Egger-Lampl, S.; Schatz, R.; D’Alconzo, A. The Logarithmic Nature of QoE and the Role of the Weber-Fechner Law in QoE Assessment. *IEEE International Conference on Communications* **2010**, pp. 1–5. doi:10.1109/ICC.2010.5501894.
22. Leila, S. QoE-based Application Mapping for Resource Management **2011**.