Multi-agent Systems for Personalized QoE-Management

Amro Najjar, Christophe Gravier, Xavier Serpaggi, Olivier Boissier

Multi-agent Systems for Personalized QoE-Management

Amro Najjar, Christophe Gravier
Université de Lyon, Jean Monnet University,
Laboratoire Hubert Curien UMR CNRS 5516
Saint-Etienne, France
fname.lname@telecom-st-etienne.fr

Xavier Serpaggi, Olivier Boissier
Université de Lyon, Mines Saint-Etienne,
Laboratoire Hubert Curien UMR CNRS 5516
Saint-Etienne, France
fname.lastname@emse.fr

***Abstract*—User satisfaction is becoming a key factor to secure the success of any online service. Quality of Experience is a subjective measure of the service quality as perceived by the user. QoE has been introduced to bridge the gap between the purely technical characteristics of QoS and user satisfaction. Recent research on QoE has shown that QoE is highly personal and influenced by multiple interrelated factors including the user expectations, preferences and cultural background. However, most existing QoE management solutions overlook the personal aspect of QoE and ignore inter-user differences despite the promise of adopting a user-centric approach. In this paper, we propose multi-agent technology as means to achieve personalized QoE-management. In particular, we propose a multi-agent architecture called EMan where each end-user is embodied by an autonomous agent that represents her personal preferences and expectations and seeks to maximize her QoE. To evaluate our approach, we use Repast, a multi-agent simulation platform. The preliminary results proves that such a decentralized multi-agent QoE-management outperforms an equivalent centralized approach both in terms of end-user satisfaction and service acceptability.**

***Keywords*-QoE, multi-agent systems, automated negotiations**

I. Introduction

A recent study of customer dynamics by Accenture showed that the majority of consumers in USA switched their service providers due to poor customer service experiences and that about 81% of these customers said that the company could have done something differently to prevent them from switching [1]. Furthermore, the same study points out that while price still has a key role in choice of provider, the customer experience is becoming equally important. This tendency is accentuated in the case of emerging markets such as cloud computing market. As more personal and interactive applications are moving to the cloud, user satisfaction is becoming a key factor determining the success of any cloud hosted service. Therefore, quality has the potential to become a key differentiator [2] since harsh competition has driven prices to near zero levels [3].

Quality of Experience (QoE) has been proposed as a subjective quality measure to assess the service quality as perceived by the end-user. The term QoE appeared in 2000's to bridge the gap between the purely technical characteristics of Quality of Service (QoS) and user personal evaluation of the service quality. The research on QoE is still in its early stages of development. For this reason, QoE literature still focuses on the conceptual domain (e.g. [4], [5]) and few practical works are proposed [4].

Yet, while subjectivity, personalization, and user preferences awareness are highly emphasized on the conceptual front, inter-user differences are overlooked in most of the existing operational QoE-management solutions since the resulting QoE function is supposed to measure the QoE of all the potential users of the service.

In this paper, we propose multi-agent technology as a platform to assist personal QoE-management. We introduce EMan a multi-agent architecture for QoE-management. The contributions of this paper are twofold:

- Multi-agent personal QoE management system where end-users are represented by autonomous agents. Each user agent possesses its decision model and utility function derived from the user's personal preferences. This allows to account for inter-user differences.
- Automated negotiation as a means to reach mutually acceptable settlements that satisfy the QoE of end-users while ensuring the Quality of Business (QoBiz) [6] of the provider.

These two proposals have been implemented and evaluated using Repast [7], a multi-agent simulation environment. The rest of this article is organized as follows. Section II reviews existing research addressing personal QoE-awareness, studies existing QoE-management solutions, and motivates our solution. Section III details the decision model of user agents. Section IV explains the negotiation process and offers a use-case scenario used later in the evaluation section (Section V).

II. Motivation & Approach

This section reviews existing studies dealing with personal aspects of QoE (Subsection II-A) and motivates the proposed multi-agent approach (Subsection II-B).

A. *Quality of Experience*

QoE is subjective and influenced by a multitude of complex and interrelated Influence Factors [8], [5]. The Qualinet white-paper [9] classifies these influence factors into System Influence Factors, Context Influence Factors, and Human Influence Factors (HIF). The latter are known to be the most complex to model because of their highly subjective nature and their relation to internal states and process. Examples of HIFs include: user expertise level, willingness to pay, preferences, expectations, and motivations [8].

In the literature [10], [11], [12], several empirical studies and subjective user tests concluded that QoE is an individual satisfaction metric and that inter-user differences should be taken into account. For instance, the results of the subjective user tests conducted in [10] show that the user attitude and her mood have a considerable impact on quality perception. Therefore, since moods and attitudes vary from one user to another, the user subjective evaluation of the service may differ accordingly. The results of the tests carried out in [11] prove that every user has her personal vision of the same service and that users do not have the same scale of expectations. Based on these results, the authors recommend to take the personal nature of quality perception in QoE-management systems in order to maximize user satisfaction. Furthermore, the authors point out that such an individualized approach to QoE-management allows for continuous adaptation to user preferences.

Both the ITU definition [13] and the Qualinet White Paper definition of QoE [9] underscore user expectations as an imperative QoE influence factor to reckon with. According to evidence from the field of customer expectation management, customer satisfaction is directly dependent on her expectations of the service quality. In particular, as discussed in [14], customers are assumed to have a couple of expectation standards they use to judge the quality of a given service. The first standard is the **desired expectation** that represents the ideal service whose utility from user's standpoint is maximum. Most of customers know that it is not always possible to fulfill their desired expectations. Consequently, they hold another low level expectation standard called the **adequate expectations** representing the threshold for acceptable service beyond which receiving the service has no interest from the user's standpoint. Thus, the utility the user obtains at this point (*i.e.* the adequate expectation) is almost zero. The **Zone of Tolerance** is the difference between the adequate and desired expectations [14]. In [12] the authors demonstrated that a given QoE model can be improved by including preferred and adequate expectations.

Thus, most works in the literature are carried out at the conceptual or empirical levels. Integrating personal user preferences and HIFs into *operational* QoE-management solutions remains limited [8].

According to [15], QoE-management is a process aiming at maximizing user satisfaction while at the same time maximizing resource efficiency and economy. The majority of QoE-management systems views this process as an optimization process conducted unilaterally by the provider [16]. Even when user subjective evaluation of the service is integrated into the optimization process, these works rely on Mean Opinion Score (MOS) or an equivalent function estimated offline prior to service delivery (e.g. [17]). However, as discussed in [18], MOS may not be enough since it fails to account for the users' diversity and their individual expectations. Furthermore, most of subjective user trails are conducted in laboratory environment. Yet, it has been shown that field results and laboratory results may differ considerably [19].

Hence, existing QoE-management works are predominantly centralized optimization solutions solved unilaterally by the provider where end-user personal evaluation of the service is either completely ignored or relies on an offline estimation. To increase the end-user participation in a decentralized QoE-management decision making, we will resort to multi-agent systems.

B. Decentralized Management of QoE

By definition, an agent is usually self-interested and is bound to an individual perspective [20], [21]. This makes agents potential candidates to represent the subjectivity of users' opinions of a given service. Typically, agents rely on utility functions to express their preferences. We consider that user agents can represent the QoE of their respective users by a utility function. Examining the definitions of utility functions and of QoE justifies this choice since both of them are tightly related to user preferences and satisfaction:

- Utility functions are a concept borrowed from economics where agents are assumed to have *preferences* [22]. A utility function maps these *preferences* into numerical values. In other words, the utility value is a measure of the level of *satisfaction* an agent receives from any basket of goods and services [23].
- The Qualinet definition of QoE considers that it "results from the fulfillment of the user's expectation with respect of *utility*/enjoyment of the application or service" [9]. Therefore, QoE research confirms that utility is tightly related to it. Furthermore, unlike earlier definitions of QoE (e.g. [13]) where it was seen as a binary measure determining the acceptability of a service, recent definitions (e.g. [9], [4]) view it as a *degree of delight or enjoyment*. Therefore, as has been also shown in QoE literature (e.g. [24], [16], [17]), utility functions are perfect candidates to represent QoE.

A multi-agent approach to QoE-management brings about several benefits. First, it allows to take diversity of users and their personal preferences into account. Second, it allows to move the user subjective evaluation of services from research laboratory and transform it into a continuous and interactive process *in situ* since users will be able, during service consumption, to express their opinions about the service to their respective agents. Third, multi-agent systems and agent learning technology offer a powerful platform that could help QoE management systems integrate complex Human Influence Factors into the process.

A technical specification [25] of the ETSI (European Telecommunications Standards Institute) proposes an agent-based architecture to implement a layered QoE model allowing for integration into legacy systems. This specification does not specify any quality model. Instead it provides users with the possibility to plug their own models into the systems as long as their code conforms to the API of the architecture. The work discussed in our article can be considered as complementary to this technical specification since our article focuses on QoE-aware agent-based user personal model. Thus, in this article, we propose multi-agent systems as a platform to scaffold a novel personalized QoE-management approach. We introduce EMan [26], a multi-agent architecture for QoE-management, and detail the user model used in the architecture.

III. QoE-Aware User Agent Decision Model

In EMan each end-user is embodied by an autonomous agent that acts on her behalf. In order to maximize the user's QoE, each agent should have its own decision model derived from the personal preferences of the user it represents. In EMan, the decision model of user agents relies on a utility function μ reflecting the preferences of the corresponding user.

We rely on findings from customer expectation management discussed in Section II to constitute the utility functions of user agents. Let sa_i be a user agent representing the user su_i. μ_{sa_i,at_j} is the utility function of sa_i that evaluates the utility obtained from a service involving only one attribute (e.g. delay) denoted as at_j. From the discussion in Section II, we can deduce the minimum value and the maximum value of μ_{sa_i,at_j}.

When the value of the attribute at_j equals to rv_{sa_i,at_j}, the worst value the user accepts for this attribute (a value that corresponds to the *adequate expectations*), the obtained utility is minimum. Similarly, when the value of the attribute at_j equals to pv_{sa_i,at_j}, the ideal value for this attribute from the user standpoint (a value that corresponds to the *desired expectations*), the obtained utility is maximum. Thus, we can write the following equation:

$$\begin{aligned} \mu_{sa_i,at_j}(rv_{sa_i,at_j}) &= 0.0 \\ \mu_{sa_i,at_j}(pv_{sa_i,at_j}) &= 1.0 \end{aligned} \tag{1}$$

Note that in the proposed model, sa_i obtains pv_{sa_i,at_J} and rv_{sa_i,at_J} from the user since, as has been shown in [27], users are usually able to verbalize their expectations (e.g. download duration of a file or the desired download speed).

Now let us deal with the form of the utility function μ_{sa_i,at_j}. Since the service attribute evaluated by this function is an objective or technical metrics (e.g. objective time), it is not necessarily linearly correlated with the service quality as experienced subjectively by the end-user. Therefore, μ_{sa_i,at_j} may not be linear.

The logarithmic hypothesis proposed by Reichl *et al.* [28] postulates that the QoE of the end-user is estimated by a logarithmic function of the QoS parameter given that the latter is directly perceivable by the user [29]. This hypothesis is based on the Weber-Fechner Law (WFL), a well known law in Psychophysics whereby the human perception of a stimulus is proportional to the logarithm of the stimulus intensity. WFL has been validated by empirical studies examining the human fives senses, time perception and human numerical cognition [28]. Note that this article does not aim to prove the logarithmic relationship. Rather, it uses this relationship as an assumption to discuss the merits of personalizing QoE-management using multi-agent systems.

The generic form of the logarithmic hypothesis maps the value of a measured QoS parameter to QoE as follows [29]:

$$QoE = -\alpha \cdot ln(QoS) + \beta$$

Where QoE is the quality of experience obtained by the end-user and QoS is the measured service parameter. In the QoE literature, the coefficients α and β are estimated by applying a curve fitting process where the MOS points, obtained via subjective user studies, are fitted into a logarithmic function [28], [30]. Therefore, the resulting logarithmic function is considered as a common relationship used to estimate the QoE of all the users.

As discussed in [29], in EMan we assume that this hypothesis holds as long as the service attributes (at_j) represent technical (*i.e.* QoS) parameters perceivable directly by the end-user (e.g. delay). However, since we adopt a multi-agent-based approach where the QoE is seen as a personal function derived from personal end-user preferences and expectations, α and β become individualized coefficients denoted henceforth as α_{sa_i,at_j} and β_{sa_i,at_j}. Therefore, μ_{sa_i,at_j} (the QoE-aware utility function of the attribute at_j) becomes:

$$\mu_{sa_i,at_j}(v_{at_j}) = \alpha_{sa_i,at_j} \cdot ln(v_{at_j}) + \beta_{sa_i,at_j} \tag{2}$$

Where v_{at_j} is the value (offered by the provider) of the attribute at_j. Then, in order to formulate the personal utility function of the user su_i, her agent sa_i can estimate α_{sa_i,at_j} and β_{sa_i,at_j} by relying on the following equation (see [26] for the complete explanation):

$$\begin{aligned} \alpha_{sa_i,at_j} &= \frac{1}{ln(rv_{sa_i,at_j}) - ln(pv_{sa_i,at_j})} \\ \beta_{sa_i,at_j} &= \frac{ln(rv_{sa_i,at_j})}{ln(rv_{sa_i,at_j}) - ln(pv_{sa_i,at_j})} \end{aligned} \tag{3}$$

If the service involves multiple attributes, M_{sa_i}, the overall utility function of the agent sa_i is defined as a weighted sum of attribute-wise utility function as follows:

$$M_{sa_i}(o) = \sum_{j=1}^{j=J} w_{sa_i,at_j} \cdot \mu_{sa_i,at_j}(o[at_j]) \tag{4}$$

Where o is an offer, proposed by the provider, that assigns a value to each one of the service attributes. $o[at_j]$ is the value of the attribute at_j. w_{sa_i,at_j} is the weight associated with attribute at_j to specify how much importance this user gives to this attribute. The weights are obtained from the user via a graphical interface. They should satisfy $\sum_{j=1}^{J} w_{sa_i,at_j} = 1$.

IV. Service Negotiation

The utility functions of user agents represent the preferences and the expectations of their respective users. Yet, the service provider has also its cost/profit and business objectives. In order to resolve the conflict arising between these potentially opposed aspirations, we will rely on automated negotiation

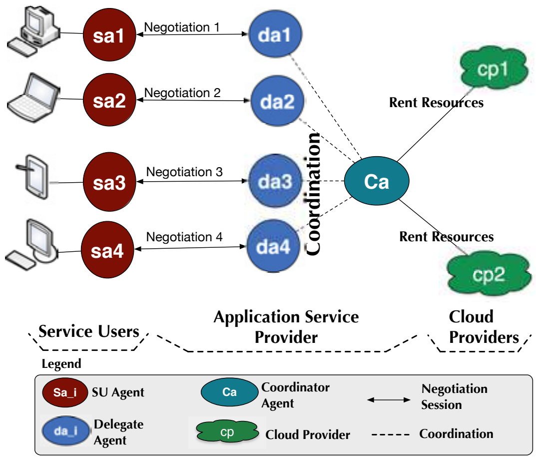

Fig. 1. EMan architecture involving both users agents and providers agents.

as a means to reach mutually acceptable settlements between user agents seeking to maximize the QoE of their users and provider agents that are mainly concerned with maximizing the Quality of Business (QoBiz) [6] of the provider. For the sake of an agreement, both parties must make tradeoffs and concessions hereby accepting to reduce the utility they obtain. The negotiation/coordination strategies used in the EMan architecture are beyond the scope of this article (c.f. [26] for a detailed explanation). Next subsection presents a use-case scenario.

A. Use-case: QoE-Aware Cloud Elasticity Management

EMan can be used in any QoE-aware service negotiation taking place between a provider on one side and end-users on the other side. Yet, in order to better explain the aim of the negotiation process, let us take an example of an Application Service Provider (ASP or SaaS provider) offering a cloud-hosted compute-intensive service (e.g. video transcoding). The ASP uses compute resources from the cloud in order to fulfill the requests of its users. The amount of virtual resources available from the cloud is elastic, virtually unlimited, and enough to handle all the clients requests in a satisfactory manner. However, the ASP is constrained by the fees it must pay to the cloud provider. Elasticity management [31] is the process aiming at reducing the cost of resources rented from the cloud while delivering a satisfactory service to the end-user. Using EMan, elasticity management results from a negotiation process involving agents representing the SUs (denoted as sa_i) and other agents representing the ASP. Figure 1 illustrates the EMan architecture when used for QoE-aware elasticity management. The provider is represented by two types of agents: delegates, each assuming a bilateral negotiation session with one user agent, and one coordinator agent.

Note that we are totally aware that the service may span several cloud and network providers. We consider that it is the ASP's responsibility to deal with these multi-operator settings. Therefore, in this use-case we focus on cloud resource management (*i.e.* elasticity management) and we consider that the underlying network is managed adequately by the ASP.

The service being negotiated in the proposed use-case can involve multiple attributes such as job completion time (JCT) and any other attributes directly perceivable by the user. In our example we will focus on the JCT. However, the same discussion applies to other attributes.

In order to estimate the *subjective* time perception of the user it represents, a sa_i relies on the WQL hypothesis. The *WQL Hypothesis* [30], derived from WFL and the logarithmic hypothesis, states that the relationship between waiting time and its QoE evaluation is logarithmic. WQL has been applied successfully to describe the impact of waiting time on the user QoE for various types of services (e.g. file download service [30]). Similarly, we assume that other attributes of the service fulfill the logarithmic hypothesis.

B. Negotiation Process

In each negotiation round, participating agents exchange offers and counter offers following a specified protocol. An offer assigns a value to each one of the service attributes. Upon receiving an offer from the ASP, a user agent should estimate the subjective utility it obtains from the offer.

At the outset of a negotiation session, a sa_i obtains $pv_{sa_i,jct}$ and $pv_{sa_i,jct}$ of the user. These values represent respectively the preferred and reservation value of this user. Then sa_i constitutes its utility function $\mu_{sa_i,jct}$ from Equations 3 and 2. The utility functions of other attributes can be formulated in a similar manner. Furthermore, sa_i gets/estimates the weights assigned by user to each one of the attributes involved in the service.

Using M_{sa_i} (the overall utility function defined in Eq 4) and its decision model, sa_i can evaluate offers received from the provider, it makes its accept/reject decision, and bids a counter offer using its negotiation strategy (e.g. making a concession). In this use-case, all sa_i agents use Time-Based Concession (TBC) strategies in which the concession made by an agent depends on the time left before reaching the time deadline T_{sa_i} for this negotiation session. If sa_i does not get a satisfying offer before reaching T_{sa_i} it breaks the negotiation process without finding an agreement. The value of T_{sa_i} is independent from the JCT and can be estimated by sa_i depending on the user preferences or on the current context.

Once a user logs into the system, the provider spawns a delegate agent da_i to negotiate with the corresponding sa_i. da_i agents have a reservation cost Rc and a preferred cost Pc specified by the provider. These values are common to all da_i agents. Rc is the maximum cost the provider accepts to spend in order to satisfy the request of a sa_i. Pc is the minimum cost dedicated to sa_i. In this use-case, the ASP gets a constant fee from the clients, for this reason, its negotiation goal is to minimize the cost spent on a sa_i so that the profit (fee minus cost) is maximized. da_i agents can use several negotiation strategies. Moreover, the ASP has a coordinator agent ca that oversees the negotiation process and intervenes in an ongoing negotiation session when necessary in order to impose the global business strategy of the ASP. Note that, as it is the case in most of negotiation processes, participants (i.e. sa_i and da_i agents) do not disclose their preferences, their strategies, nor their reservation values. Due to space limitations, we will not detail the negotiation/coordination processes nor the performance model of the provider. Further details can be found in [26].

Next section details the evaluation process and discusses the results.

V. Evaluation

We use Repast [7], to evaluate the results obtained by the EMan architecture. In each simulation round we launch 1000 user agents representing each a different user. Each user agent has its own preferred and reservation values for each one of the attributes involved in the service. This satisfies the conclusions drawn in [14] where it has been postulated that the Zone of Tolerance varies from one client to another. In the simulation these values are generated randomly as follows: $pv_{sa_i,jct} \in [2, 6]$ minutes, $rv_{sa_i,jct} \in [20, 30]$ minutes. Other attributes are generated in a similar manner. The negotiation time deadline of user agent is generated randomly.

User agents log into the system following a Poisson process whose mean arrival rate is $A = 4$ users per minute. The parameters on the ASP side are as follows: $Rc = 2.0$\$ and $Pc = 1.0$\$. The fee the ASP obtains from users is $fee = 3.0$\$. Due to space limitations, we will not discuss results from ASP standpoint. Further details can be found in [26].

The aim of the evaluation process is to compare the result obtained by the multi-agent QoE-management approach against the result obtained by a comparable centralized approach where the ASP takes the QoE-management decision unilaterally. The evaluation process is organized as follows:

- **Step 1**: We use the multi-agent QoE-management approach (*i.e.* the EMan architecture) with a given provider negotiation strategy. The results of this step are: *(i)* metrics indicating user satisfaction (average subjective utility obtained by sa_i agents denoted as $\bar{M}$, out: percentage of users who reached their negotiation time deadline and quit before getting a satisfactory service), *(ii)* $\bar{c}$ the average cost spent by the ASP per user.
- **Step 2:** This step is designed to emulate existing (MOS-based) centralized works in the literature. In order to have comparable results with Step 1, in Step 2 the ASP offers a service whose cost is $\bar{c}$ per gold user ($\bar{c}$ is obtained from Step 1). Based on $\bar{c}$, the ASP can propose a set of tradeoffs to the users. A tradeoff is proposed when an agent shifts the value of some of attributes in its preferred direction while shifting the values of other attributes in the direction supposedly preferred by the opponent. The provider uses a global MOS function to choose the best offer from the set of tradeoffs. This function is computed by averaging the utility functions of the same user agents from Step 1. Thus, from ASP standpoint, this function is an objective estimation of the QoE of all the users of the service. The ASP uses it to select the offer that is supposed to be the best for the users under the given cost constraint (*i.e.* $\bar{c}$). The selected offer is then delivered to all users without any negotiation. The results of this experiment are *(i)* the objective utility estimated by the ASP using the global provider function (denoted as $centr$) *(ii)* using the personal utility functions computed as explained in Section III, we calculate $\bar{M}$, the average of the subjective utility obtained by users measured using their personal utility functions, and *(iii)* out the percentage of users who rejected the service offered by the ASP because it failed to satisfy the minimum of their expectations.
- **Step 3**: This step is designed as an enhancement of Step 2. The latter does not allow users to participate in the QoE-management process. For this reason, it is likely that less users will find the service offered by the ASP to be acceptable (i.e. above their adequate expectations). Consequently, the actual average, denoted as $\bar{c}_{real}$, will likely be lower than $\bar{c}$. In Step 3, the ASP strategy in Step 2 is upgraded so that the cost saved when one user rejects the service is reinvested to serve other incoming users. Thus, $\bar{c}_{real}$ remains equivalent to $\bar{c}$.

TABLE I
Evaluation Results

/	$\bar{M}$	out	$\bar{c}$	$\bar{c}_{real}$	$centr$
Step 1	0.42	7.7%	1.384	1.384	NA
Step 2	0.28	55%	1.384	0.72	0.38
Step 3	0.44	34%	1.384	1.384	0.6

Note that the metric out measures the percentage of user agents (sa_i) who reached their negotiation time deadline before getting a service offer whose utility is at least equivalent to their adequate expectations. Thus, out is very important since it allows to quantify acceptability.

The first row of Table I lists the results of Step 1. The negotiation strategy of the ASP spent 1.384\$ per user. This was enough to fulfill the adequate expectations of the majority of users since the results show that more than 90% of users found the service to be acceptable or better. Note that the value of $\bar{M}$ can only be taken relatively and cannot be converted to the 5-point scale designating the categories: "bad", "poor", etc. since, in our model, obtaining a utility slightly above 0.0 is considered acceptable (and therefore equivalent to *fair* on traditional MOS scale).

The second row of the table lists the results of Step 2 where the ASP relied on global function estimated by averaging utility functions to emulate a centralized MOS estimation similar to works in the literature. The results show that when the ASP decides to invest $\bar{c} = 1.384$ \$ (an investment equivalent to that in Step 1) the utility of the offer it delivers to the users is estimated by the ASP as $centr = 0.38$ on average. However, from users' subjective perspective, the average obtained utility is only $\bar{M} = 0.28$. More importantly, upon receiving the offer imposed by the ASP, about 55% of the users rejected the service (out=55%). Because of this high outage rate, the actual average cost spent per user is $\bar{c}_{real} \approx 0.72$ \$ since less than half of the 1000 users accepted the service.

The results of Step 3 show that when provider strategy of Step 2 is upgraded to reinvest the surplus generated by users rejecting the service (i.e. $\bar{c}_{real} \approx 1384$ \$), $\bar{M}$ increases considerably since some users are getting an excellent service. However, about of a third of users ($out = 34\%$) found the service to be unacceptable. Thus, Step 3 achieves a $\bar{M}$ equivalent to that of Step 1. However, the high outage rate shows that it lacks the flexibility required to account for user diversity and their subjective visions of the service.

Comparing the metrics $centr$ and $\bar{M}$ in Step 2 or in Step 3 suggests that the MOS function formulated by the ASP in this use-case tends to over-estimate the QoE delivered to users. This observation need to be investigated in future research.

The preliminary results discussed above indicate that, compared with the centralized ASP-driven approach, the proposed multi-agent approach is able to take user diversity and personal user preferences into account. Thus, it leads to better user satisfaction and better service acceptability rate.

VI. Conclusion & Future Works

In this article we argued that Multi-agent systems provide an efficient platform able to scaffold a personalized & decentralized QoE-management approach. The end-user personal evaluation of the service and their expectations is integrated into the decision making by means of automated negotiations. The results of the simulation proves that such a decentralized multi-agent QoE-management outperforms an equivalent centralized approach both in terms of end-user satisfaction and service acceptability.

Future works will be focused on integrating more HIFs (e.g. user expertise) and Context Influence Factors into the user agent decision model. To this end, QoE-aware agent learning techniques will be investigated to model the evolution of user preferences and experience across time.

References

[1] Accenture, "Accenture 2013 global consumer pulse survey global & u.s. key findings," Dublin, Ireland, 2013.

[2] T. Hobfeld, R. Schatz, M. Varela, and C. Timmerer, "Challenges of qoe management for cloud applications," *Communications Magazine, IEEE*, vol. 50, no. 4, pp. 28–36, 2012.

[3] D. Durkee, "Why cloud computing will never be free," *Commun. ACM*, vol. 53, no. 5, pp. 62–69, May 2010. [Online]. Available: http://doi.acm.org/10.1145/1735223.1735242

[4] S. Möller and A. Raake, *Quality of Experience*. Springer, 2014.

[5] K. U. R. Laghari and K. Connelly, "Toward total quality of experience: A qoe model in a communication ecosystem," *Communications Magazine, IEEE*, vol. 50, no. 4, pp. 58–65, 2012.

[6] A. Van Moorsel, "Metrics for the internet age: Quality of experience and quality of business," in *Fifth International Workshop on Performability Modeling of Computer and Communication Systems*, vol. 34, no. 13, 2001, pp. 26–31.

[7] N. Collier, "Repast: An extensible framework for agent simulation," 2003.

[8] U. Reiter, K. Brunnstrm, K. De Moor, M.-C. Larabi, M. Pereira, A. Pinheiro, J. You, and A. Zgank, "Factors influencing quality of experience," in *Quality of Experience*, ser. T-Labs Series in Telecommunication Services, S. Mller and A. Raake, Eds. Springer International Publishing, 2014, pp. 55–72.

[9] K. Brunnström, S. A. Beker, K. De Moor, A. Dooms, S. Egger, M.-N. Garcia, T. Hossfeld, S. Jumisko-Pyykkö, C. Keimel, C. Larabi *et al.*, "Qualinet white paper on definitions of quality of experience," 2013.

[10] I. Wechsung, M. Schulz, K.-P. Engelbrecht, J. Niemann, and S. Möller, "All users are (not) equal-the influence of user characteristics on perceived quality, modality choice and performance," in *Proceedings of the Paralinguistic information and its integration in spoken dialogue systems workshop*. Springer, 2011, pp. 175–186.

[11] A. Lavignotte, C. Gravier, J. Subercaze, and J. Fayolle, "Quality of experience, a very personal experience!" in *2013 24th International Workshop on Database and Expert Systems Applications*, Aug 2013, pp. 231–235.

[12] A. Sackl and R. Schatz, "Got what you want? modeling expectations to enhance web qoe prediction," in *Quality of Multimedia Experience (QoMEX), 2014 Sixth International Workshop on*. IEEE, 2014, pp. 57–58.

[13] I. T. U. ITU, "Definition of Quality of Experience (QoE) ITU-T FG IPTV (Study Period 2005) Liaison Statement (Incoming) 50," 2007.

[14] V. A. Zeithaml, L. L. Berry, and A. Parasuraman, "The nature and determinants of customer expectations of service," *Journal of the academy of Marketing Science*, vol. 21, no. 1, pp. 1–12, 1993.

[15] R. Schatz, M. Fiedler, and L. Skorin-Kapov, "Qoe-based network and application management," in *Quality of Experience*. Springer, 2014, pp. 411–426.

[16] S. Thakolsri, W. Kellerer, and E. Steinbach, "Qoe-based cross-layer optimization of wireless video with unperceivable temporal video quality fluctuation," in *Communications (ICC), 2011 IEEE International Conference on*. IEEE, 2011, pp. 1–6.

[17] G. Gómez, J. Lorca, R. García, and Q. Pérez, "Towards a qoe-driven resource control in lte and lte-a networks," *Journal of Computer Networks and Communications*, vol. 2013, 2013.

[18] T. Hobfeld, R. Schatz, and S. Egger, "Sos: The mos is not enough!" in *Quality of Multimedia Experience (QoMEX), 2011 Third International Workshop on*. IEEE, 2011, pp. 131–136.

[19] R. Schatz and S. Egger, "Vienna surfing: assessing mobile broadband quality in the field," in *Proceedings of the first ACM SIGCOMM workshop on Measurements up the stack*. ACM, 2011, pp. 19–24.

[20] K. P. Sycara, "Multiagent systems," *AI magazine*, vol. 19, no. 2, p. 79, 1998.

[21] M. Wooldridge, *An introduction to multiagent systems*. John Wiley & Sons, 2009.

[22] J. Wilkes, "Utility functions, prices, and negotiation," *Market Oriented Grid and Utility Computing. Wiley Series on Parallel and Distributed Computing*, pp. 67–88, 2008.

[23] D. Besanko and R. Braeutigam, *Microeconomics*. John Wiley & Sons, 2010.

[24] G. Aristomenopoulos, T. Kastrinogiannis, V. Kaldanis, G. Karantonis, and S. Papavassiliou, "A novel framework for dynamic utility-based qoe provisioning in wireless networks," in *Global Telecommunications Conference (GLOBECOM 2010), 2010 IEEE*. IEEE, 2010, pp. 1–6.

[25] ETSI TS, *ESI TS 103 294 v1.1.1 Speech and multimedia Transmission Quality (STQ); Quality of Experience; A Monitoring Architecture,*, 2014.

[26] A. Najjar, "Multi-agent negotiation for qoe-aware cloud elasticity management," Ph.D. dissertation, École nationale supérieure des mines de Saint-Étienne, 2015.

[27] A. Sackl and R. Schatz, "Evaluating the impact of expectations on end-user quality perception," in *Proceedings of International Workshop Perceptual Quality of Systems (PQS)*, 2013, pp. 122–128.

[28] P. Reichl, S. Egger, R. Schatz, and A. D'Alconzo, "The logarithmic nature of qoe and the role of the weber-fechner law in qoe assessment," in *Communications (ICC), 2010 IEEE International Conference on*. IEEE, 2010, pp. 1–5.

[29] R. Schatz, T. Hoßfeld, L. Janowski, and S. Egger, "From packets to people: quality of experience as a new measurement challenge," in *Data traffic monitoring and analysis*. Springer, 2013, pp. 219–263.

[30] S. Egger, P. Reichl, T. Hosfeld, and R. Schatz, "time is bandwidth?? narrowing the gap between subjective time perception and quality of experience," in *Communications (ICC), 2012 IEEE International Conference on*. IEEE, 2012, pp. 1325–1330.

[31] A. Najjar, X. Serpaggi, C. Gravier, and O. Boissier, "Survey of elasticity management solutions in cloud computing," in *Continued Rise of the Cloud*. Springer, 2014, pp. 235–263.