Prospect Theoretic Pricing For QoE Modeling In Wireless Multimedia Networking

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***Abstract*—One of the biggest challenges in wireless multimedia communications is to provide satisfactory Quality of Experience (QoE) to the users. Recently, numerous QoE maximization metrics and techniques have been proposed to jointly improve the network performance and user satisfaction. However, these methods are built upon postulates of Expected Utility Theorem (EUT). In this paper, we discuss the limitations of EUT in modeling QoE and explore the nuances in Prospect Theory (PT) such as asymmetrical s-shaped value function and reference point dependence to develop a prospect-theoretic QoE maximization framework by incorporating price in QoE model. An algorithm to determine the amount of data that users should purchase at any given cost such that their QoE is maximized, is also presented. As an exemplary scenario, we consider a simplified multimedia communication network with two users, where both users request the same multimedia content and aim to achieve the best possible QoE. Traditional EUT-based price-QoE model has been adopted for the first user, while the proposed PT-based prospect theoretic multimedia pricing QoE model has been used for the second user. Simulation studies conducted with H.265 multimedia codec data reveal that PT user achieved higher QoE in comparison to EUT user at a lower cost. Results also indicated that PT-based modeling can improve system throughput and network revenue.**

***Index Terms*—Quality of Experience (QoE), Smart Media Pricing, Prospect Theory.**

I. Introduction

With multimedia becoming the predominant traffic in wireless communication networks with enormous increase between 2017-2022 [1], improving the Quality of Experience (QoE) observed by the users is of paramount importance. The human perception of QoE is a complex function that varies from one service to another, and is also a context dependent function that depends upon the pervious and subsequent services. Therefore, researchers have always found it difficult to come up with a concrete mathematical model to describe QoE in wireless multimedia communications.

Expected Utility Theorem (EUT) has been widely used to develop QoE models in the past. However, EUT assumes that people are introspective, rational and uninfluenced by real life situations while making a decision. Kahneman and Tversky revealed that the decision-making ability of human under risk, violate the fundamentals of EUT and presented a critique called Prospect Theory (PT) [2]. Shortcomings of EUT and precepts of PT that quantify the QoE from a human phycological standpoint are discussed in detail in section II.

Recently, Smart Media Pricing (SMP) [3] was introduced based on the idea of leveraging price-QoE in wireless multimedia network protocol scheduling. SMP was built upon traditional QoE model based on rate distortion and power distortion by adding price as a third dimension. In this work, we take a step further by integrating PT to the SMP model to develop Prospect Pricing, which possesses a potential to further improve the network performance in terms of throughput and revenue.

In order to test the efficiency of the proposed framework, we consider a wireless communication setting with two users and a base station as shown in Fig. 1. QoE models incorporating economic price using EUT and PT has been developed for EUT user and PT user respectively. The detailed devising of QoE model is presented in section III. The users, under similar channel condition, request same multimedia using certain encoding schema based on their QoE model and base station encodes the content using the schema decided by users and transmit it to them.

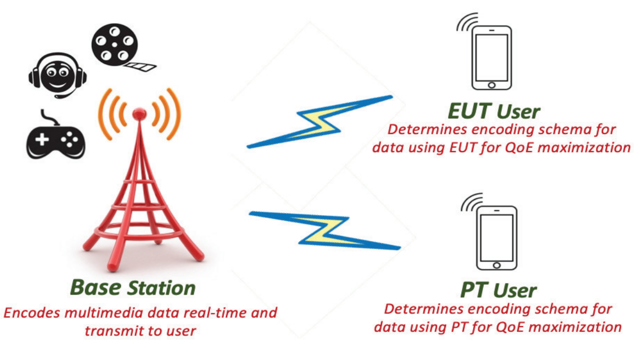

Fig. 1. System Model - QoE maximization - EUT user versus PT user

The QoE maximization problem is then translated into an optimization problem where both users determine the encoding schema, in terms of multimedia frame length (bits), to purchase for the price announced by the base station. The flexibility provided by H.265 video encoding technique has been leveraged to code multimedia content of varying data sizes [4]. Concave optimization techniques and an algorithm based on the rudiments of PT have been used to achieve the optimality of the EUT and PT user respectively. The solution to the optimization problem is elaborated in Section IV.

Several researchers in the past have devised QoE models to simultaneously improve network profits and user satisfaction. Profit-driven QoE model for HetNets with differential services [5], Markov decision process-based network assisted

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mobile streaming [6], multimedia resource allocation [7] and downlink power level optimization in non-orthogonal multiple access wireless multimedia [8] have been proposed. However, these QoE models do not evaluate user satisfaction from a human psychological point of view.

Last decade has withnessed an increasing number of researchers from various fields exploring PT. However, not until recently PT has been applied to the study of wireless communications. Authors in [9] and [10] have applied PT to psychologically model wireless network access among users and end-user subjective perceptions in autonomous wireless communications. These models however do not consider user perceptions to be continuously shifting dynamic function. In this research, similar to [11], we have used dynamic value function to model QoE function of the user.

II. Prospect Theory

Kahneman and Tversky presented a critique of Expected Utility Theory (EUT) called Prospect Theory (PT), which modeled the human decision-making behavior. A paradox to explain deviation of EUT, developed by Kahneman and Tversky [12] has been tabulated below.

TABLE I
Illustration : Decision-making violates EUT

	Choice A	*Choice B*
Game 1	80% chance to win \$4000	Sure win of \$3000
Game 2	20% chance to win \$4000	25% chance to win \$3500

Examining game 1, a player has 80% chance of winning \$4000 and a 100% chance of winning \$3000 by choosing A and B respectively. Therefore, under EUT, the player gets a utility of \$3200 (0.80 X 4000) and \$3000 (1 X 3000) by playing choice A and B respectively. Similarly, in game 2, a player has 20% and 25% of winning \$4000 and \$3500 by playing choices A and B. EUT yields a utility of \$800 and \$875.

The games shown in table above were presented to 100 random participants. It was observed that 80% of the respondents choose choice B in game 1. This result which contradicts EUT also demonstrates the risk-aversive behavior of human preferring sure win to a probable one. Interestingly, 65% responded with choice A for game 2, illustrating the risk-seeking attitude of people for low probable events. These results create a paradox which cannot be modeled using EUT.

PT classifies the biases observed in decision making into certainty effect (risk aversion), loss aversion and isolation effect. The certainty effect states that human tend to be risk aversive for gains by overweighting options that are highly-probable or certain (as observed in results of game 1). It is the inherent nature of mankind to behave in a certain way that would minimize the loss even if the probability of losing is minimal. In the process of minimizing losses, players tend to become risk seeking and gamble over a sure loss. This effect is called loss aversion. Isolation effect is the people's tendency to disregard the options that are common in both the choices. The German phycologist Hedwig Von Restorff documented isolation effect as the stimulus that differs from the rest and which is most likely to be remembered when multiple stimuli are presented [13].

In order to mathematically formulate the distortions caused due to human cognition, PT provides the weighting function, value function and reference point dependence to capture the effects of risk aversion, loss aversion and isolation.

A. Weighting Function

The decision-making probabilities are always measured linearly under EUT. However, human tend to overweight low probability and underweight high probabilities in an effort to minimize losses. PT introduces a non-linear probability weighting function to map true probabilities to subjective probabilities and is governed by *proposition 1* stated below.

Proposition 1: *A weighting function has the following properties: (a)* $w(0) = 0$ *and* $w(1) = 1$*. (b)* w *has a unique inverse,* w^{-1}*, and* w^{-1} *is also a strictly increasing function* $w(\varepsilon) : [0, 1] \xrightarrow{onto} [0, 1]$*. (c)* w *and* w^{-1} *should be continuous.*

B. Value Function

Losses hurt human more than gains excite them. PT postulates an asymmetrical and s-shaped value function to capture this loss aversive effect. The characteristics of the value function are specified in *proposition 2*.

Proposition 2: *A value function has the following properties: (a) value function is defined on the deviations from the reference point; (b) generally concave for gains and convex for losses; (c) steeper for gains than for losses.*

C. Reference Point

The value function captures the human valuation on a given outcome based on profits and losses about a set reference point. The choice of reference point significantly affects the valuation of the user perceived value function. The inflection point in the value function is decided by the reference point. A typical weighting function and value function is shown in Fig.2. below.

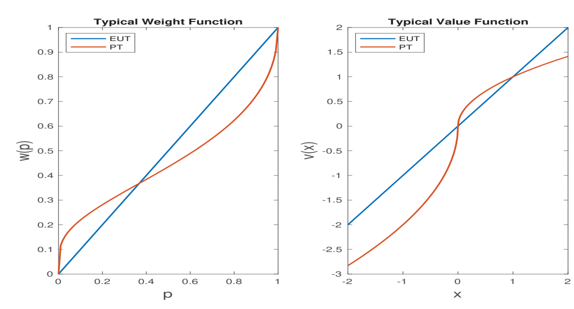

Fig. 2. Typical weighting and value function as prescribed by PT

III. System Model

The primary objective of this research is to mathematically quantify the QoE of the user from PT perspective and compare it with EUT based model. In this section, we first define EUT based QoE model by assimilating price-based SMP protocol and later show how to meaningfully integrate PT to our definition. We then introduce PT based dynamic value function as a suitable paradigm to model subsequent interactions in wireless multimedia communication and finally present our problem formulation.

A. SMP based QoE definition

QoE is a per-session measure of user satisfaction in terms of utility maximization. In each session, the consumer requests a sequence of multimedia frames denoted by $i = 1, 2, ..., N$. SMP recommends QoE to be modelled based of on rate, power and price distortion. Accordingly, we define the rate distortion in terms of Packet Error Rate (PER), and multimedia quality described by Peak Signal to Noise Ratio (PSNR). PSNR is expressed using the frames quality contribution q_i and the contributions from its ancestor frames $k \in \pi_j$. Power distortion is defined as product number of bits in the frame and amount of power transmitted by the base station to transmit the bit P_{BS}. Finally, y_i is the per bit cost of multimedia data paid by the consumer to obtain service. The QoE function can be formulated using a two-level logarithmic model, [7], and it is given by equation(1).

$$\begin{aligned} &QoE^{SMP} = \\ &\log\left(1 + \sum_{i=1}^{N} L_i \left(\alpha q_i \prod_{k\in\pi_j} (1 - P_k) \log(1 + \beta P_{BS})\right)\right) \\ &- \sum_{i=1}^{N} L_i y_i \end{aligned} \tag{1}$$

The length of the frames (in bits) is denoted by L_i and PER $P_k = 1 - (1 - BER)^{l_k}$ is defined as the number of packets in error after forward error correction divided by the total number of received packets l_k. The parameters α and β are positive values used to align the rate and power distortion to currency values. This EUT based SMP-QoE model will be leveraged by the EUT user in the two-user wireless communication scenario shown in Fig.1.

B. Prospect Theoretic QoE Definition

While evaluating the user QoE, people are more sensitive to losses than to gains. In order to capture the loss aversion characteristic among consumers, we have used the asymmetric value function as defined in [12] to model our QoE.

$$v(x) = \begin{cases} x^{\kappa}, & \text{for } x \geq 0 \\ -\lambda(-x)^{\kappa}, & \text{for } x < 0 \end{cases} \tag{2}$$

where k and λ are positive parameter which controls the shape of the function and steepness of the function in loss region.

The value function shown above has a loss region and gain region and the point of inflection, also called as reference point, is centered at origin. Therefore, reference point becomes critically important while using PT to formulate problems, as it affects the valuation.

In a typical wireless communication setting, the base station announces the cost of providing service y_i and user decides amount of data L^* to purchase at any given cost. The base station delivers requested content using the encoding scheme requested with a power distortion and rate distortion suitable to the current channel conditions. If the consumer receives data(bits) $\widehat{L}_i \geq L^*$, he/she is more satisfied and so the observed QoE is in gain region. Similarly, if received data $\widehat{L}_i < L^*$, due to channel conditions or other technicalities, then perceived QoE is in loss region. In conclusion, L^* is a suitable reference point for our QoE model and can be integrated to the value function as shown in equation (3).

$$QoE^{PT} = \begin{cases} L^* QoE^{SMP} & \widehat{L}_i \geq L^* \\ -\lambda\left(-L^*\right)^{QoE^{SMP}} ; & \widehat{L}_i < L^* \end{cases} \tag{3}$$

C. Prospect Theoretic Dynamic QoE Function

The reference point is time-varying and gets updated based on the multimedia content requested and channel conditions. The QoE equation shown above therefore has a dynamic point of inflation which can be computed using game theory or machine learning techniques. Similar to the reference point, the value function also is time varying. For example, if a person expects to win \$1000 in a lottery but wins \$1100, he/she feels happy and once again in the second round of lottery they expect to win another \$1000 but win \$1100, he/she feels happier. Although the gain exceeded by a same margin of \$100 both times, the happiness quotient of the person is higher during the second win. Therefore, if the base station transmits some $\widehat{L}_i \geq L^*$ for two consecutive services, the perceived QoE of the user during second service is much higher than the first service, although same quality of service was delivered successively. This is true for two or more consecutive service losses as well. In order to capture this effect, we adopt the dynamic value function model developed in[11].

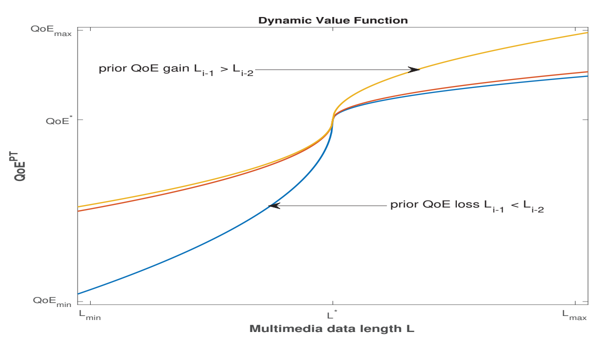

Fig. 3. Dynamic value function for QoE modeling

$$QoE^{PT} = \begin{cases} \begin{cases} \mu_1 \; L^* QoE^{SMP}; & \widehat{L}_i \geq L^* \\ -\lambda\left(-L^*\right)^{QoE^{SMP}} ; & \widehat{L}_i < L^* \end{cases} & \hat{L}_{i-1} > \hat{L}_{i-2} \\ \\ \begin{cases} L^* QoE^{SMP}; & \widehat{L}_i \geq L^* \\ -\lambda\left(-L^*\right)^{QoE^{SMP}} ; & \widehat{L}_i < L^* \end{cases} & \hat{L}_{i-1} = \hat{L}_{i-2} \\ \\ \begin{cases} L^* QoE^{SMP}; & \widehat{L}_i \geq L^* \\ -\lambda\mu_2\left(-L^*\right)^{QoE^{SMP}} ; & \widehat{L}_i < L^* \end{cases} & \hat{L}_{i-1} < \hat{L}_{i-2} \end{cases} \tag{4}$$

The QoE evaluation function becomes steeper towards gain region after experiencing QoE gain in previous service and becomes steeper towards loss region after pervious QoE loss as shown in the equation (4) below. This dynamic QoE model (visualized in Fig.3) is used by the PT user described in Fig.1.

D. Problem Formulation

The optimization problem can be formulated as maximizing QoE subjected to the overall multimedia constraint. $L_{i_{\min}}$ and $L_{i_{\max}}$ are the minimum number of bits required to encode the requested data and maximum available resource with the base station for providing service respectively. The goal of our work is to determine the optimal value for multimedia content L_i^* to purchase such that QoE^{PT} is maximized.

$$\begin{array}{ll} \text{maximize} & \sum_{i=1}^{M} QoE^{PT} \\ \text{s.t.} & L_{i\,\min} < L_i^* < L_{i_{\max}} \end{array} \tag{5}$$

IV. QoE Maximization Solution

In this section, we derive strategies for both EUT and PT user to maximize their individual QoE. We do so by translating the maximization problem into an optimization problem. The derived strategies are unique and can be applied to any multimedia communication setting and frame cost y_i announced by the base station.

A. EUT solution for QoE maximization

The goal of the EUT user is devise a strategy to determine the amount of multimedia data to purchase at any given cost that would maximize their QoE. The maximization problem can be translated into an optimization problem and optimality can be achieved using property 1.

Property 1: *A continuous and real QoE equation within a close interval is concave when the price rate y_i is fixed has a unique maximum value which can be determined by equating its first derivative to zero.*

Validation: We begin by computing the first and second derivatives of QoE^{SMP} function as shown in equations (6) and (7). Since the QoE equation is both real and differentiable, it has to be continuous within the closed interval $[L_{i_{\min}}, L_{i_{\max}}]$. Now by examining the second order derivative (equation (7)), we can observe that all terms in the equation are squared and so the function $\frac{\partial^2 QoE^{SMP}}{\partial L_i^2}$ is negative at all times. Therefore, the function is concave and the optimal value for L_i^* that maximizes the QoE function can be determined by equating the first derivative to zero.

$$\frac{\partial QoE^{SMP}}{\partial L_n} = \frac{\sum_{i=1}^{n} \alpha q_i \Pi_k \in \pi_j (1-P_k) \log(1+\beta P_{BS})}{\sum_{i=1}^{n} L_i\left(\alpha q_i \prod_k \in \pi_j (1-P_k) \log(1+\beta P_{BS})\right)+1} - \sum_{i=1}^{n} y_i \tag{6}$$

$$\frac{\partial^2 QoE^{SMP}}{\partial L^2} = -\frac{\sum_{i=1}^{n} \alpha^2 q_i^2 \prod_{k \in \pi_j} (1-P_k) \log^2(1+\beta P_{BS})}{\left(\sum_{i=1}^{n} L_i\left(\alpha q_i \prod_k \epsilon_{\pi_j} (1-P_k) \log(1+\beta P_{BS})\right)+1\right)^2} \tag{7}$$

The optimal multimedia frame size for EUT user is $\sum L_i^*$. However, it is unreasonable and realistically impossible for all frames to be encoded and transmitted at the optimal length L_i^*. Therefore, optimality is achieved by taking an equality condition $\sum_{i=1}^{N} L_i^* = L^*$ and now by equating the first order derivative to zero, we have the optimal strategy for the EUT user as shown in equation (8).

$$L^* = \frac{\sum_{i=1}^{n} \alpha q_i \prod_k \epsilon_{\pi_j} (1-P_k) \log(1+\beta P_{BS}) - y_i}{\sum_{i=1}^{n} y_i \left(\alpha q_i \prod_k \in \pi_j (1-P_k) \log(1+\beta P_{BS})\right)} \tag{8}$$

During implementation, EUT user shall compute the optimal data length values for all possible price values set by the base-station and form a two-dimensional look-up table. The best value for multimedia frame length is chosen from the table ahead of each service flow.

B. Prospect Theoretic solution for QoE maximization

The solution derived in previous section optimizes the QoE^{SMP} function. Since EUT assumes user to be rational and uninfluenced by external factors, the solution derived is optimal in a perfect world. PT based model is built upon the QoE^{SMP} function to make it more relevant from an economic and cognitive standpoint. Therefore, PT based model becomes significant after few initial rounds of transmission. The PT user begins the multimedia transactions using data length L^* (EUT solution) derived earlier and then L^* is further optimized for subsequent interactions using the postulates of PT using the Lemma 1 shown below.

Lemma 1: *When the value function follows the postulates of prospect theory prescribed in proposition 2, the optimal value for $\sum_{i=1}^{N} L_i^* = L^*$ that maximizes the QoE has to be a monotonically increasing function.*

Validation: Let L_1^* and L_2^* be the amount of data purchased by the user using the equation (8) during two subsequent services with QoE_1^{SMP} & QoE_2^{SMP} being the actual value for quality of experience. Firstly, considering a case where user perceived satisfaction evaluated using the PT framework is $QoE_1^{PT} > QoE_2^{PT}$. Now, during the third transaction, the user purchases L_3^* such that $L_1^* < L_3^* < L_3^*$. This can result in two scenarios: $a)$ $QoE_1^{SMP} < \overline{QoE_3^{SMP}} < QoE_2^{SMP}$ and $b)$ $QoE_1^{SMP} < QoE_2^{SMP} < \overline{QoE_3^{SMP}}$. Now, by using PT value function to compute the user perceived satisfaction, it can be observed $\overline{QoE_3^{PT}}$ is always smaller than QoE_3^{PT} due to the s-shaped value function which is steeper in the loss region. Thus, QoE can be maximized if and only if the function $\sum_{i=1}^{N} L_i^* = L^*$ is monotonic.

Secondly, considering the case where the $QoE_1^{PT} < QoE_2^{PT}$, equation (4) specifies subsequent interactions to be evaluated with a value function shifted towards gain region. Hence for QoE to be maximized, the value function must remain in the gain region $s.t.$ $QoE_2^{PT} < QoE_3^{PT}$ and amount of resource purchased should be non-zero. Therefore, the function has to be monotonically increasing.

Using Lemma 1 and other channel constrains, we present an iterative algorithm as Algorithm 1. to determine a strategy to maximize the QoE for PT user.

Algorithm 1 Prospect theoretic QoE maximization

1) **Functionality:**
The algorithm determines an optimal multimedia content buying strategy based on the previous service provided, for the PT user for maximizing their QoE.
2) **Initialization:**
   2.1. Initialize the QoE model parameters α, β, μ_1 and μ_2.
   2.2. Define channel and GOP characteristics: bit error rate BER, transmission power P_{BS}, multimedia quality q_j and their corresponding lengths l_j.
3) **Iterations:**
   3.1. PT user uses the L^* determined using equation 8 for initial few iterations.
   3.2. Define iteration limit M, computation interval $L = linespace[L_{min}, L_{max}, M]$ and multimedia step-size L_{step}.
   3.3. For j=1:M : iterate and determine L_i^* using equation 8.
   3.4. Compute QoE_{SMP} and QoE_{PT} using equations 1 and 4.
   3.5. **if** $\boldsymbol{QoE^{PT}_{n-1} > QoE^{PT}_{n-2}}$**:**
      3.5.1 Set $\overline{L}_i^* = L_{i-1}^* + L_{step}$
      3.5.2 Compute $\overline{QoE}^{PT}$ using $\overline{L}_i^*$
      3.5.3 **if** $\boldsymbol{\overline{QoE}^{PT} \geq QoE_{PT}}$**:** Announce $\overline{L}_i^*$ as L_i^* and break.
      3.5.4 **else :** update $\overline{L}_i^* = \overline{L}_i^* + L_{step}$. Go to step 3.5.2
   3.6. **if** $\boldsymbol{QoE^{PT}_{n-1} < QoE^{PT}_{n-2}}$**:**
      3.5.1 Set $\overline{L}_i^* = L_i^* + L_{step}$
      3.5.2 Compute $\overline{QoE}^{PT}$ using $\overline{L}_i^*$
      3.5.3 **if** $\boldsymbol{\overline{QoE}^{PT} \geq QoE_{PT}}$**:** Announce $\overline{L}_i^*$ as L_i^* and break.
      3.5.4 **else :** Update $L_i^* = L_i^* + L_{step}$. Go to step 3.5.2
   3.7. **else:** Announce $\boldsymbol{L_i^* + L_{step}}$ as optimal strategy and break.

V. Simulation Study

In order to validate the efficiency of developed PT QoE maximization framework and to test its competence against the EUT model, simulation studies were conducted using MATLAB. The compressed video data was obtained using $H.265$ coder and the following simulations were carried out.

The two users considered in our study, follow the QoE models shown in equations (1) and (4). For the first simulation, we have considered an ideal channel with SNR of $30dB$. The bit error rate (BER) was set at $1e-6$ and the initial values for α and β are 0.1 and 4 respectively. For a fixed multimedia base price $y_0 = 0.4$, the QoE for both the users have been simulated. From Fig.4., it can be observed that the PT user achieves higher QoE by purchasing lesser data from the base station under same channel characteristics.

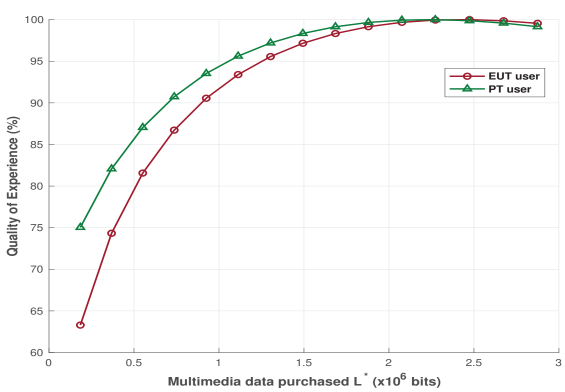

Fig. 4. Quality of Experience - EUT user versus PT user

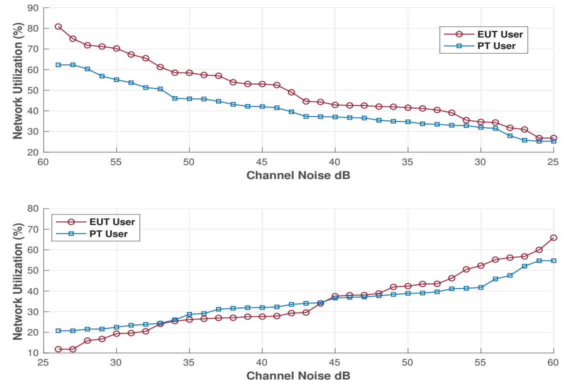

Fig. 5. Network utilization against channel noise - EUT user versus PT user

The distortion in human cognition is captured using PT. In order to model the distortion, we have considered two channels in Fig.5. In Fig. 5(a), we consider a recovering channel where the channel noise decreases during the communication. As the channel condition improves, the users can achieve higher QoE by purchasing lesser data. The amount of data transmitted by the base station is directly proportional to the network utilization and so as the conditions convalesce, the network utilization decreases. PT advocates that users are happier during subsequent gains and their QoE goal can be achieved by purchasing lower data than the EUT user. Therefore, PT based approach works flawlessly in a recovering channel.

In Fig 5(b), we consider a monotonically deteriorating channel where the channel noise increases during the multimedia communication. We proved that the amount of data purchased by the user has to be a monotonically increasing function to improve the QoE of the user. Therefore, it can be observed that network utilization gradually increases for the PT user. It can be observed that the EUT user performed better initially, this is due to the loss aversion (risk-seeking) attitude of the PT user. The user ends up utilizing more resources, hoping to maximize their utility. The graphs also illustrate that base station is able to achieve higher profits by catering the PT user.

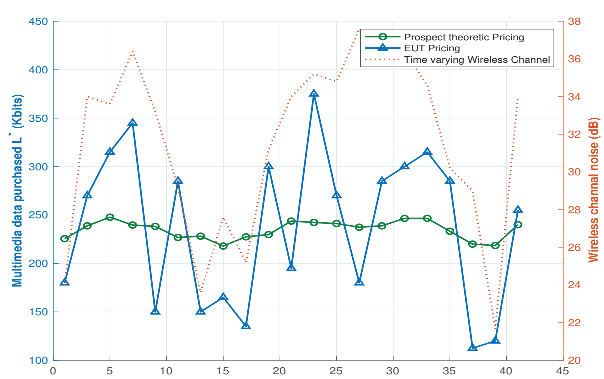

Fig. 6. Analysis over a time varying channel - EUT user versus PT user

PT user performed significantly better in a recovering channel while EUT user seemed to have an upper hand in communication happening over a deteriorating channel. In reality, the channel is continuously time varying and to test for competency, we consider a time-varying wireless channel. From Fig. 6, it can be observed that the amount of data requested by the EUT user fluctuates so much, making it hard for the user to achieve the QoE goal. In contrast, PT ensures that the QoE of users is not compromised due to channel quality.

VI. Conclusions

In this paper, we have restructured the SMP pricing QoE model from prospect theoretic perspective, taking into account the user psychological effect. The s-shaped asymmetric value function has been used to describe the variation of user perceived QoE from its actual value. We then adopted existing dynamic value function to model QoE in subsequent multimedia transactions. A QoE-maximization game between an EUT user and a PT user was investigated to evaluate the competence of proposed model. Simulation results indicated improvement of QoE for the user and significant reduction in network utilization, implying higher profit potentials for the base station by utilizing the saved network resources.

VII. Acknowledgement

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