Human Cognition Aware QoE For NOMA Pricing: A Prospect-Theoretic Augmentation To Non-Orthogonal Wireless Multiple Access

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***Abstract*—Human cognition has become a fundamental metric to evaluate the Quality of Experience (QoE) and service provided in modern day communication systems. Expected Utility Theorem (EUT) is widely used to mathematically model human behavior and analyze decision-making process. However, studies carried out in literature reveal that the decision-making ability of users under certain circumstances, violate the precepts of EUT and proposed an alternative model called Prospect Theory (PT). On the other hand, Non-Orthogonal Multiple Access (NOMA) has been advocated as a new promising technique to improve network capacity performance. In NOMA research, issues such as congestion control and power allocation have been the primary focus and end-user QoE has largely been ignored. In the past, we have designed a NOMA pricing framework to simultaneously boost user QoE and base station profits while addressing the other issues of power selection and resource allocation. The primary focus of this paper is to introduce the new prospect-theoretic postulates to the NOMA pricing framework to further study the user QoE in wireless multimedia services. The prospect-theoretic QoE model for NOMA communication has been derived using the weighting function and value function. Further, we have simulated a NOMA network to evaluate the efficacy of the developed prospect-theoretic QoE model. Simulation results exemplify the potentials of prospect-theoretic QoE modeling of NOMA pricing framework in wireless multimedia communications.**

***Index Terms*—Non-Orthogonal Multiple Access Pricing, Quality of Experience, Prospect Theory.**

I. Introduction

Non-Orthogonal Multiple Access (NOMA) is an emerging network access technique and has been widely investigated as a potential candidate to mitigate the explosive boom in internet-ready devices and improve the communication systems efficiencies [1]. In power-domain NOMA communication [2], the available spectrum is split into several resource blocks with varied characteristics in terms of throughput and latency. The service provider then groups several users together in each of the available resource blocks. The data of all the users in a block are superimposed and encoded at varied power levels. The transmission of such a superimposed signal allows the service provider to provide faster service to higher number of users, resulting in a significant boost in spectral efficiency.

Strategic choice of power distribution among users, non-uniform pricing of NOMA resource and resource allotment are some of the existing open issues. In previous works we have introduced NOMA Pricing (NOMAP), a novel pricing framework for NOMA wireless communications to address part of the open issues, in order to boost the end-user QoE and service provider profits [3, 4]. Under NOMAP, the users were given a free choice to strategically determine the NOMA resource block(s) to utilize for data transmission. NOMAP also facilitated the service providers to have a dynamic non-uniform pricing schema where the resource blocks could be priced based on external factors such as interference, congestion and network demand. The users can also determine the amount of encoding power to purchase to save money and also meet their QoE demands based on Expected Utility Theorem (EUT) . This pricing of QoE approach facilitates users to achieve satisfactory service quality, and enables the base station to attain higher profits. EUT has been widely used in QoE modeling of wireless communication systems and is also the underlying philosophy of NOMAP. The fundamental shortcoming of EUT is that it assumes the users to be rational and uninfluenced by external factors. 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) [5]. The human psychological risk seeking, and risk aversion behaviors can be captured using the weighting and value function as prescribed in PT.

Human cognition aware PT has been gaining excessive attention among the investigators in the field of wireless communication and multimedia networks. PT was used to capture the underlying rationality among players in secure unmanned aerial vehicles (UAVs) communication [6]. In the research works [7] and [8], the authors have applied PT to psychologically model wireless network access among users and end-user subjective perceptions in autonomous wireless communications. PT pricing models are also being investigated to boost network revenue. Resource pricing and allocation in MEC-enabled blockchain systems was investigated using deep reinforcement learning and PT to strike a good balance between risks and rewards [9]. Dynamic value and weighting functions have also been explored to capture human cognition of risks and losses [10]. In this work, we have meaningfully incorporated the postulated PT into our NOMA pricing framework to further study the end-user QoE.

The rest of this manuscript is organized as follows. In section II, we introduce the prospect-theoretic NOMAP framework and provide the utility definitions. The optimization solution is briefed in section III and an algorithm is presented as an implementation reference. We carried out simulation on MATLAB to study and evaluate the performance and the results are discussed in the section IV. We provide conclusions and insights into the probable future work in Section V.

II. Prospect-Theoretic NOMA Pricing Framework

In this work, we consider a NOMA network with 'm' resource block and 'n' users in each block. All 'n' users in the block are catered simultaneously by superimposing their signals over one another at varied power levels. The users then recover their data from the complex signal using successive interference canceller. The user closest to the base station would have their data at the top of the carrier signal and so would experience no interference from other user data. As the distance from the base station, and number of users between end-user and base station increase, the data is subjected to more interference. Therefore, these signals need to be encoded with higher power. Under NOMAP framework, the user gets to choose the resource block and amount of power to purchase in the corresponding user block to maximize their overall QoE.

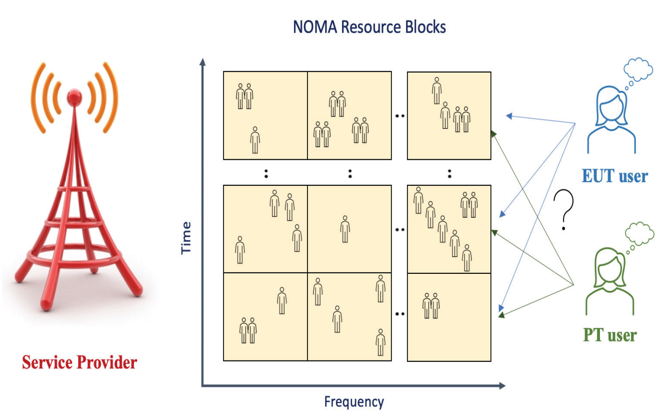

Fig. 1. Prospect Theoretic NOMA Pricing Concept

The NOMAP network considered in this work is illustrated in Figure 1 above. NOMAP provides the user with a free choice of block and power selection. Two rational users named EUT user and PT user are considered in this figure. It is assumed that both users request the same data and have identical QoE demand. In our previous work based on EUT QoE model [3], we found out that a user's choice of resource block is insignificant as the price is different in each block. In other words, the EUT user was always able to meet their QoE goals by varying the amount of power purchased in any of the resource block. The objective of this work is to see if the PT user might prefer one block over the other to either achieve better QoE gain or, to save money.

In order to formulate the behavior of the PT user mathematically, we leverage the PT postulates - weighting function, value function and the reference point dependence. This would capture the risk seeking, loss aversion and isolation behavior of humans under stress [11]. PT uses weighting function to map true probabilities to subjective probabilities of events. The weighting function [5] of PT is shown in equation (1).

$$w(\epsilon) = \exp\left(-\beta(-\ln \epsilon)^{\alpha}\right), 0 < \epsilon \leq 1 \tag{1}$$

where ϵ is the true probability of user choosing resource block m and $w(\epsilon)$ is the PT subjective probability. α and β are positive coefficients used to control the shape of weighting function. The user QoE is dynamic and changes rapidly. While evaluating the user QoE, users are more sensitive to losses than to gains. This phenomenon is called loss aversion and this can be mathematically captured using a value function. The value function [5] is shown in equation (2).

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

where κ and λ are positive parameters controlling the shape and steepness of the value function respectively. The x_m^* is the expected gain by the user and x_m is the actual achieved gain. The gain of the user x_m in the NOMA network is per-session measure of user perceived satisfaction and it can be modeled using a two-level logarithmic function.

$$x_m = \gamma \log_2\left(1 + B\log_2\left(1 + \frac{P_i\left|h_i\right|^2}{\sum_{k=j+1}^{N} P_k\left|h_k\right|^2 + \sigma^2}\right)\right) - C \tag{3}$$

where B is the amount of bandwidth purchased to transmit data. P_i and h_i denote the power transmitted and channel gain between base station and end user, respectively. The noise power in the communication channel is given by σ^2. The interference experienced by the user is the summation of P_k and h_k corresponding to k users closer to the base station. The parameter γ represents the payoff parameter or currency gain for the logarithmic QoE and C represents the total cost paid by user to obtain this service.

The QoE of the user in a wireless network can be represented the product of probability of user choosing one of the available resource blocks and the actual value of gain from the resource block.

$$QoE = w\left(p_m\right) v\left(x_m\right) \tag{4}$$

III. Optimization Solution and Algorithm Design

In a NOMA network, the two player interaction between service provider and the end user can be modeled as a game theoretic problem. Stackelberg game can be used for concave [3], and Best Response game can be used for non-concave [4] utility equations respectively. The games are generally solved backward induction technique, and so the service provider knows the strategy of the user and can determine the right price for the resource blocks. The strategies for the service provider to maximize the revenue are widely studied both in the literature and in our previous work. Finding the preeminent solution or pricing policy for the service provider is not part of this research. In this work, we strive to find and optimize a strategy for the end-user exploiting PT.

The optimization problem for the PT user is to determine the optimal amount of power P_i corresponding to the cost C declared by the service provider for the m^{th} resource block. The optimal value for P_i lies between P_{min} and P_{max}. P_{min} denotes the minimum power required to meaningfully encode the data and transmit. The maximum power that the base station can allot for user i in resource block m is limited by P_{max}. Such an optimal value for power P_i is determined for possible resource blocks which the user can utilize for data transmission.

Algorithm 1 Power optimization and resource block selection - PT-NOMAP

1) **Initialization:**
   - 1.1. Initialize all the system parameters for the weighting function (α, β) and the value function (κ, λ)
   - 1.2. The total number of resource blocks is given by m. Each of the resource blocks are initialized with different values for noise σ and number of users n_m. The users closer to the base station than the end user introduce interference h.
   - 1.3. The total number of power options between P_{min} and P_{max} is given by u. The step size between P_{min} and P_{max} can be reduced to save computational time, or increased to obtain best solutions. The total number of transmission (groups of data purchased) is given by u
2) **Iterations:**

   For: Each of the resource blocks m

   For: number of power intervals between P_{min} and P_{max}

   compute the optimal value for the power P_i using equation (3)

   compute the QoE for the user using equation (4)

   choose the resource block with highest QoE gain m^*.

   if: $QoE_n \geq QoE_{n-1}$ [case 1: risk seeking]

   then: Set P_i^* = P_i + P_{step}

   Declare P_i^* as power to purchase and m^* as the choice of resource block.

   else if: $QoE_u < QoE_{u-1}$

   if: $P_i < P_{i-1}$ [case 2a: isolation]

   Declare P_i as power to purchase and m^* as the choice of resource block.

   if: $P_i \geq P_{i-1}$ [case 2b: loss aversion]

   Set $P_{max} = P_{i-1}$

   Recompute the optimal value for power between new P_{min} and P_{i-1}

   choose the resource block with best QoE as m^*

   Declare new P_i as power to purchase and m^* as the choice of resource block.

   end For

   end For
3) **Output:** The optimal power to purchase P_i* and the resource block m to join for each of the u services.

The two level logarithmic utility definition model introduces concavity to the gain function x_m. This can easily be validated by taking the second order derivative for the function. For the initial few rounds of transmission the optimized value x_m^* is determined from the equation (3). Since the gain function is concave, the optimal value for P_i that would yield highest possible utility can be determined by equating the first order derivative to zero. Once the optimality is achieved, the PT QoE equation (4) is be evaluated to determine the perceived experience. Whenever we have a value function that follow the postulates of PT, the optimal $\sum_{i=1}^{N} P^* = P_i^*$ that maximizes the QoE equation has to be a monotonically increasing function [12]. Therefore, the optimality can be achieved by choosing a monotonically increasing values of power for the end user.

Since the PT value function equation (2) used in this research is concave for gains, convex for losses, and steeper for losses than for gains, allocating more resource at the current transmission than at the previous and/or subsequent transmission opportunities would result in significantly less QoE. Therefore, in this paper we use a curve smoothing function which limits the PT user from rapidly altering the amount of transmission power purchased for data transmission. An algorithm to determine the optimality for the PT user is discussed considering the risk seeking, loss aversion and isolation behavior of humans. When the channel conditions are favorable [case 1], the users tend to go all-out to achieve even higher QoE. This captures the risk-seeking attitude. When there is a loss [case 2b], the user becomes primitive and tries to reduce further losses. And finally when the loss is so bad [case 2a], the user tends to pretend that nothing went wrong and does nothing. The algorithm is presented as Algorithm 1.

IV. Simulation Results and Discussions

The developed optimization solution was put into test over a minimalistic NOMA network. The simulation was carried out in MATLAB to validate the efficiency of the proposed PT-NOMA pricing against the EUT-NOMA pricing and EUT-uniform pricing (tradition pricing scheme). The coefficients for the weighting function were initialized to be $\alpha = 0.5$ and $\beta = 5$ respectively. The coefficients for the value function were initialized at $\kappa = 0.5$ and $\lambda = 3$ respectively. The minimum and maximum SNR considered for the simulation were $2dB$ and $60dB$. The cost parameter in the gain equation was set as $\gamma = 10$.

In the Fig. 2 (top), EUT based NOMAP solution is compared against proposed PT optimized NOMAP solution. The transmission channel is assumed to be time varying with additive white gaussian noise. The wireless channel causes rapid fluctuation in the EUT solution. A large increase in resource allocation followed by a large decrease in resource allocation corresponding to noise results in significant user dissatisfaction due to the steeper curve at the loss region of the value function in equation (2). PT optimization on the other hand reduces the fluctuations in user data by strategically smoothing out the transmission power. It is also worth noting that the user satisfaction is close to a monotonically increasing function which we strive to achieve for best utility.

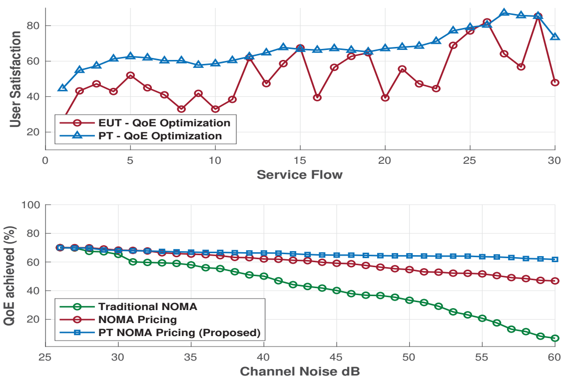

Fig. 2. Evaluation of Prospect Theoretic NOMA Pricing

In Fig. 2 (bottom), the QoE achieved is compared against channel noise. In the traditional method, the QoE drops with increase in noise. In NOMAP, since the data is priced based on the channel conditions, the user has an option to purchase more power as the channel conditions worse. The additional power purchased at lower cost helps NOMAP user to achieve better QoE. The prospect theoretic solution on the other hand is an acquisitive approach to keep user QoE stable in a time varying channel. Therefore, the PT user can achieve best QoE using the prescribed PT NOMAP model. However, it is worth noting that the PT user expends more money (buys more power) than an EUT user to achieve the attainable QoE.

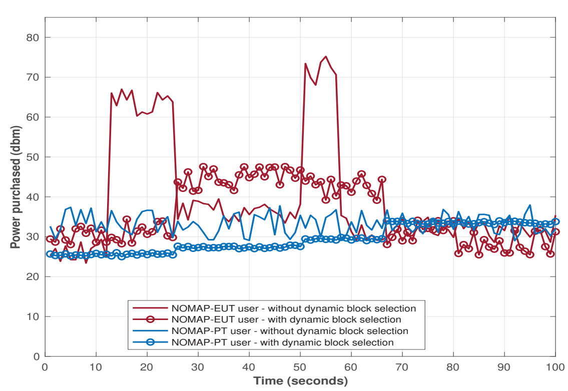

Fig. 3. Analysis of power purchasing behavior for random noise

The amount of power purchased by the user translates to the QoE the user can achieve. In Fig 3., the optimal power required for achieving highest utility for both EUT and PT user is captured. The analysis was carried out on a high interference - high throughput link. The result was captured with and without allowing to users to switch between different resource blocks. It can be observed that the results for the EUT user without dynamic block selection had high fluctuation. This is because the user adapts and purchase varying power to nullify the affect of rapidly changing noise. The two curves for PT user are significantly better as the user tends to keep switching blocks between services to attain constant QoE. From the figure, it can also be inferred that the PT user with dynamic block selection purchased the least amount of power to achieve same QoE as the EUT user.

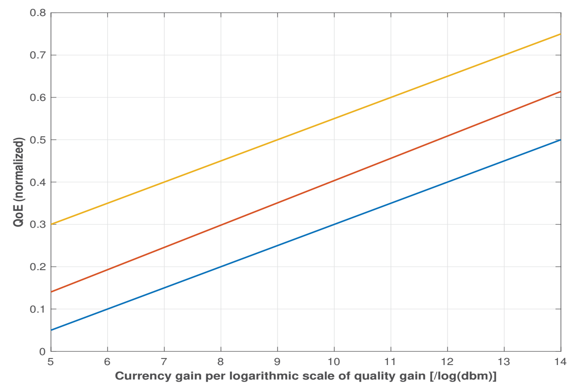

Fig. 4. Comparison of QoE with various currency gain per logarithmic scale of quality gain

The gain function x_m has a positive cost parameter γ to convert the gain to cost. Simulation were carried out to study the impact of cost parameters on the overall QoE and the results are captured as Fig. 4. Three different curves are shown in the figure for various simulation parameter. It can be observed that all the curves increase linearly. Thus, the different initializations of the parameters do not affect the the solution or outcome the the proposed PT-NOMAP scheme always achieve high QoE gain.

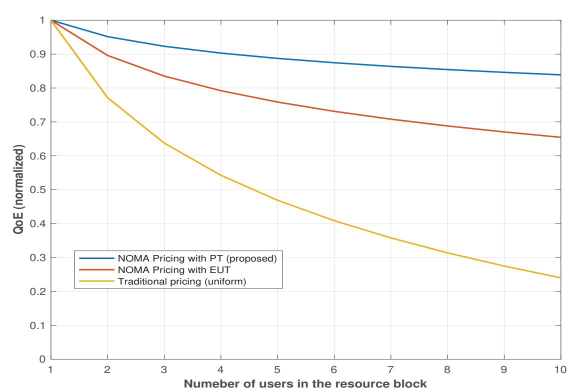

Fig. 5. Evaluation for QoE with increase in number of users (interference) in a NOMA resource block

The NOMA resource blocks are dynamic: new users may join and existing users could leave a block at any given time. Therefore it is vital to study the impact on the QoE with respect to the number of users in a resource block. Simulation was carried out by increasing the number of users between the end-user and base station (introducing interference). From the Fig 5., it can be observed that the EUT user without NOMAP (traditional pricing) is highly impacted by the number of users. This is due to the uniform pricing scheme implemented where the user pays the same amount of money irrespective of number of users in the resource block. The NOMAP reduces the impact on the QoE as cost of power goes down with increase in interference. The NOMAP with PT nullifies the impact much better. This result illustrates the future potentials of PT based NOMA pricing scheme for power-domain NOMA communications.

V. Conclusions and Future Works

Extensive boom in wireless communication and falling network spectral efficiency demands a need for efficient network access schemes. Although NOMA is a promising technology, key issues such as dynamic pricing and strategic resource allocation are remaining open challenges. In our previous work, we introduced NOMAP - a novel QoE pricing framework for power-domain NOMA communication. The NOMAP aims to simultaneously boost the end user experience and service provider profits. PT has been gaining attention among investigators to psychologically model human cognition of service satisfaction and QoE. In this work, we have exploited the value function and weighting function from PT to further study the NOMAP framework. The utility definitions are defined and the optimization solutions are discussed. An algorithm has been provided for implementation reference. The NOMAP framework with and without the PT rules were examined in a simulated NOMA network. The results indicate a significant decrease in transmission power purchased to meet QoE needs using PT. NOMAP with PT also yields better user satisfaction in a dynamic setting and the results further attests the incorporation of PT fundamentals in QoE modeling.

As for the future work, we would be investigating the potentials of dynamic value and weighting function in QoE modeling. With multimedia being the predominant traffic on the wireless networks, we are also exploring the potentials of introducing PT to generalized QoE models for multimedia communication. This would possibly allow the users to have a control over the encoding schema, packet length and compression coefficients.

VI. Acknowledgement

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