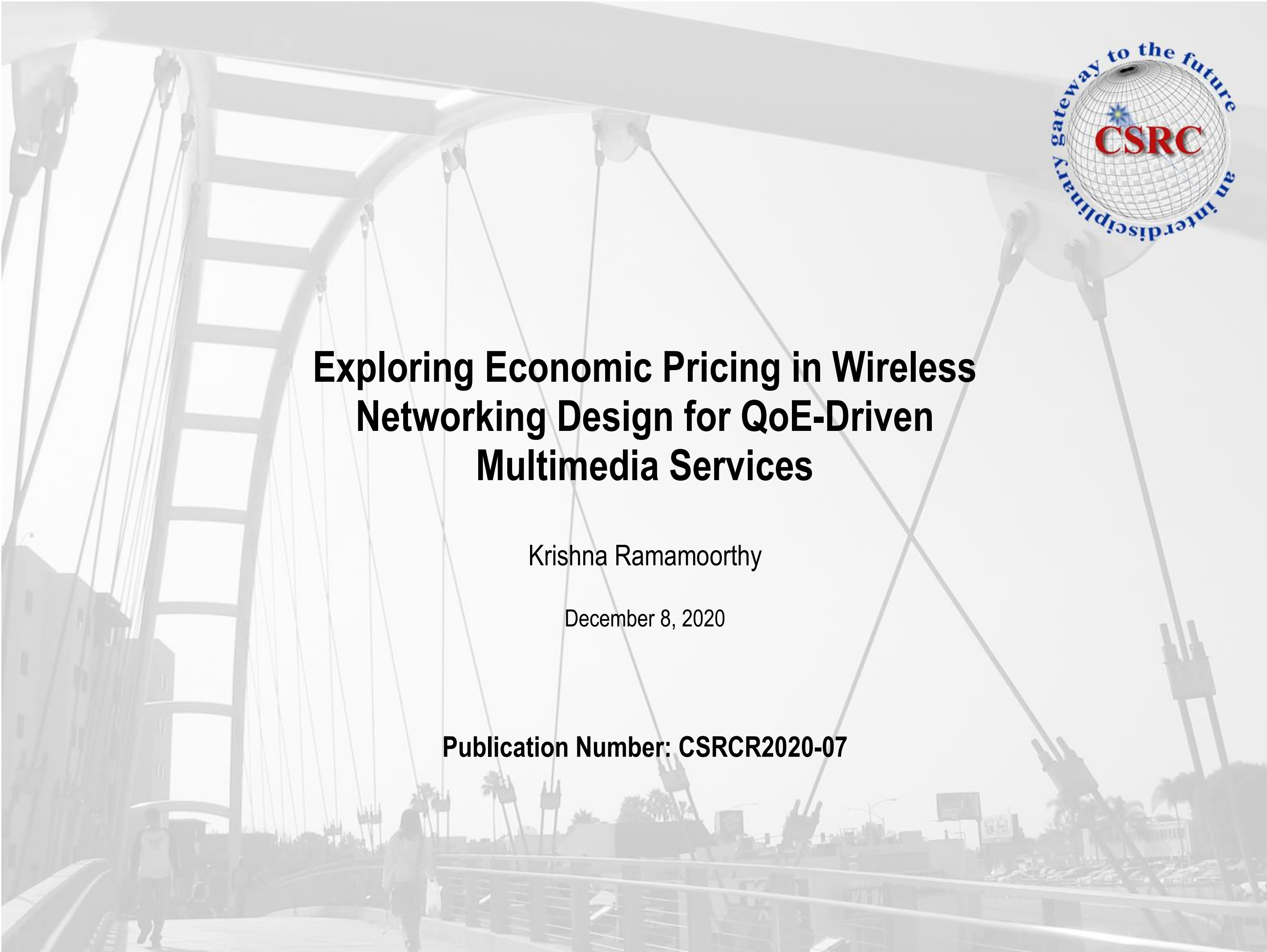

Exploring Economic Pricing in Wireless Networking Design for QoE-Driven Multimedia Services

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Exploring Economic Pricing in Wireless Networking Design for QoE-Driven Multimedia Services

submitted in partial fulfillment of the requirements for the Research Report Examination for the degree of Doctor of Philosophy in Computational Science

By

Krishna Murthy Kattiyan Ramamoorthy

Dec 2020

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KMK Ramamoorthy and W. Wang, "QoE-Sensitive Economic Pricing Model for Wireless Multimedia Communications Using Stackelberg Game," *in proc. IEEE Global Communications Conference (GLOBECOM),* Dec. 2019.

KMK Ramamoorthy, W. Wang and K. Sohraby, "Stackelberg Game-Theoretic Spectrum Allocation for QoE-Centric Wireless Multimedia Communications", in Edge Computing – EDGE 2019, Lecture Notes in Computer Science, vol 11520. Springer, Cham, June 2019.

ABSTRACT

One of the biggest challenges in wireless multimedia communications is to provide satisfactory Quality of Experience (QoE) to the users. With increasing number of mobile users, leveraging economics in communications has been envisioned as a new paradigm to boost the network performance. Smart Multimedia Pricing (SMP), a resource allocation approach based on pricing the Quality of Experience (QoE) rather than the binary data traffic, has shown the potential of improving the end user QoE and maximizing the profit of service providers.

In this work, we first we chalk up a SMB based QoE-sensitive multimedia data pricing economic model, by pricing the quality of the data rather than the quantity of the data. The QoE model proposed is complex, parametrized and three-dimensional as it is defined in terms of Peak Signal to Noise Ratio (PSNR), Packet Error Rate (PER) and user's personal preference. The QoE model is introduced to a typical multimedia service model consisting of service provider, wireless carrier and end users. Using EUT driven game theoretic methods, Stackelberg game in particular, we mathematically translate the profit-driven interaction between the three parties. Nash equilibrium solution is derived, and simulations were performed. The results indicate the efficacy of the proposed methodology.

The user's personal multimedia content preference used to model the QoE equation is a psychological function of the content relevance, attention and mood. Traditionally, Expected Utility Theorem (EUT) has been used to mathematically model human behavior and analyze decision-making process. EUT states that people are introspective, rational and uninfluenced by external situations while evaluating a matter of interest. However, the studies carried out by Kahneman and Tversky reveal that the decision- making ability of humans under certain circumstances, violate the precepts of EUT. Therefore, in this work, we use PT to convert the true multimedia preference to human-perceived preference to mimic the user's real-life introspection. We use value function as prescribed by PT to model multimedia content preference. In addition, we also propose to use a dynamic value function to model the subsequent wireless multimedia communication interactions. In this work, we derive Nash Equilibrium solution was derived and compared it to SMP EUT solution. Simulation results suggest a significant boost in PT user QoE and exemplify the importance of prospect- theoretic modeling of multimedia preferences.

CHAPTER 1: EUT BASED QOE-SENSITIVE WIRELESS MULTIMEDIA PRICING MODEL USING STACKELBERG GAME

With advances in wireless multimedia communication technologies and the rise in end-user experience expectations, meeting the Quality of Experience (QoE) requirements of the mobile multimedia user has become challenging for content providers and wireless carriers. In this chapter, we chalk up a QoE-sensitive multimedia data pricing economic model, by pricing the quality of the data rather than the quantity of the data. Utility maximization problem between the content provider (sells multimedia content), wireless carrier (provides transmission service) and the mobile user (requests multimedia data) is modeled using the proposed framework. We then formulate the aforementioned problem as a two-stage Stackelberg game and derive the Nash Equilibrium using backward induction method. Simulation study show that each player can obtain optimal strategy where the Stackelberg equilibrium exists stably. Finally, the proposed smart pricing mechanism was tested against the traditional uniform pricing scheme and the simulation results indicate that better utilities can be achieved by leveraging the proposed scheme.

1.1 BACKGROUND

The current Cisco Visual Networking Index (VNI) forecast projects global IP traffic to nearly triple from 2017 to 2022. Virtual Reality (VR) and Augmented Reality (AR) traffic are expected to increase 12-fold between 2017 and 2022 globally, a CAGR of 65 percent [1]. With such explosive growth in multimedia traffic, meeting the QoE requirement of the mobile user becomes the biggest concern for content providers due to bandwidth constraints. This is because low multimedia quality leads to poor QoE which in turn leads to reduced usage of the applications/ services and hence reduced revenues [2].

Digital video compression techniques have been predominantly used in multimedia communication. High Efficiency Video Coding (HEVC), also known as H.265 is the state-of-the-art video compression standard in which the video is divided into GOP (Group of Pictures) and encoded. Each encoded video stream contains I (Inter frame), P (forward predicted frames) and B (bi-directional predicted frames). The B frames can be predicted or interpolated from an earlier and/or later P frame while the P frame can be predicted from the I frame [3]. I frames are more important than P frames because the transmission errors of I frames will infect the successful transmission of subsequent P frames. Therefore, the multimedia frames have unequal importance. Different multimedia packets have different bandwidth requirements and different communication energy consumption attain certain QoE for the end user [4].

Recently, Smart Media Pricing (SMP) was conceptualized to price the QoE rather than the binary data traffic in multimedia services [5]. In this research chapter, we leverage the concept of SMP to chalk up a QoE-sensitive multimedia pricing framework, to allocate price according to the quality of multimedia frames purchased by / transmitted to the mobile user.

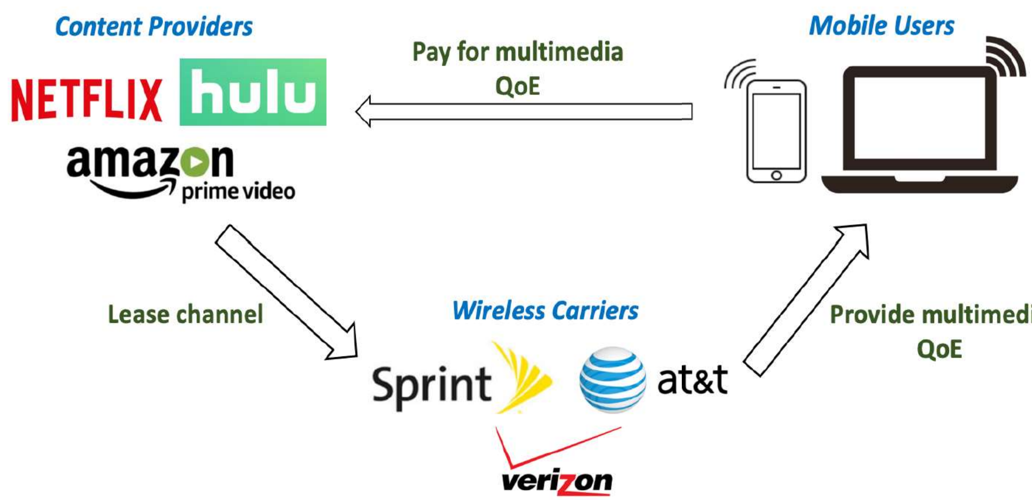

Fig 1.1 An illustration of three-party economic service model in wireless multimedia communications.

Fig. 1.1 above shows the typical economic multimedia service model in wireless multimedia communication. The mobile user requests multimedia content with certain QoE requirement and pays the content provider. The content provider leases the channel from wireless carriers to transmit the requested content. The wireless carrier allocates resources to the mobile user to provide the multimedia service at requested QoE level. In this chapter, we propose a Stackelberg game based decision-making scheme to determine the equilibrium between the cost paid by mobile user and multimedia quality achieved.

There has been rapid evolution in pricing practices among Internet service providers (ISPs) in the U.S. and other international markets, particularly in moving away from flat-rate pricing to improve their revenue [6]. Several pricing concepts such as priority pricing, Paris-Metro pricing, smart-market pricing, responsive pricing, expected capacity pricing, edge pricing, and effective bandwidth pricing have been proposed to tackle issues of network congestion and profit maximization [7]. These methods, however, do not take into consideration several important parameters such as, multimedia quality achievable under same network condition and user's personal multimedia content preference.

Smart media pricing for allocating price according to multimedia distortion reduction [4] and wireless multimedia relay communication to provide incentives to devices participating in content forwarding [9] have been investigated. The service model between provider, carrier and mobile users was modeled as a best response game and Nash Equilibrium was derived for the non-concave utility function [8]. In this chapter, we focus on developing a multimedia quality aware pricing strategy to achieve the pledged QoE for the mobile users.

1.2 QOE CENTRIC SMP - SYSTEM MODEL

The three-party interaction shown in Fig. 1 is reduced into a two-party game, by integrating the content provider – wireless carrier alliance (in short, provider – carrier alliance). The provider and carrier typically negotiate a deal behind the scene and form an alliance. Therefore, the interplay between the provider-carrier alliance is not the scope of this research. The Fig. 1.2, shows the interaction between the provider – carrier and the mobile user. In the proposed model the provider-carrier dynamically decide the cost per bit y_j for requested multimedia data. Since each frame has unequal importance, the mobile user has the flexibility to determine the number of bits y_j to purchase at any given cost.

The multimedia QoE achieved by the user is determined by the number of bits purchased. Fig. 1.2, also shows the relationship between I, P and B frames. Therefore, for a lower cost y_j, the user is willing to purchase the B frames and P frames which maximize their QoE whereas at a higher cost, the user is interested only in purchasing the I frame. In this section, we define the utilities of the provider-carrier alliance and the mobile user.

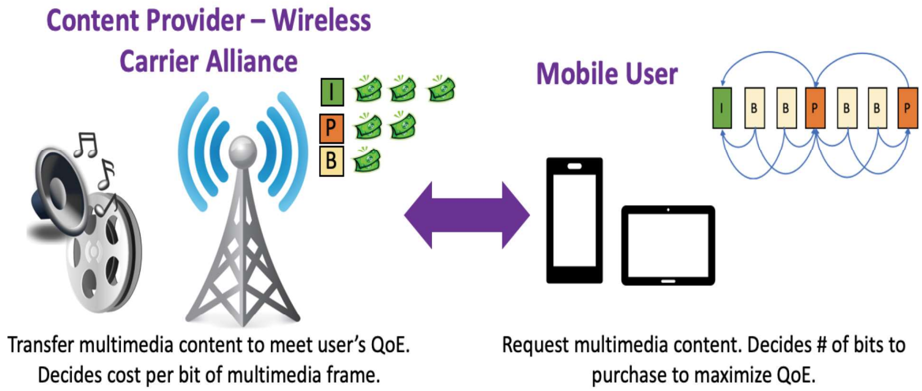

Fig 1.2 System model for smart data pricing in QoE centric wireless communications.

1.2.1 UTILITY OF MOBILE USER

The mobile user requests a sequence of frames j= {1,2, …, m} with unequal importance from the content provider over the wireless channel offered by the wireless carrier. The QoE is defined as a function of multimedia media quality described by Peak Signal to Noise Ratio (PSNR) and the Packet Error Rate (PER). The PER P_k is defined as the number of error packets after forward error correction divided by the total number of received packets. P_k is related to the Bit Error Rate (BER) and the bit length of the corresponding packet l_k.

$$P_k = 1 - (1 - BER)^{l_k} \tag{1}$$

Let q_j and l_j denote the multimedia quality and the bit length of the j^th frame. The set of ancestor frames which the j^th frame refers to is denoted by π_j. For each frame j, the QoE is related to the multimedia quality, bit length and the successful transmission probabilities of its ancestor frames and can be modelled as a logarithmic function [2]

$$QoE = a_1 \log\left(a_2 \sum_{j=1}^{m} q_j \, l_j \prod_{k \in \pi_j} (1 - P_k) + a_3 \gamma + a_4 \right) \tag{2}$$

where a_1, a_2, a_3 and a_4 are positive system parameters used to fine-tune the QoE model and γ is the user's personal preference of a certain multimedia content. For example, some users could have a greater affinity towards a soccer match video, while some users may not be interested in soccer at all. These users would have different values for γ. The effect of γ on the QoE model is further discussed in the simulation study.

The mobile user pays content provider with ψ_{user} for delivering multimedia QoE. This can be modeled as the product of the cost per bit of data transmitted y_j and the amount of multimedia transaction bits l_j.

$$\psi_{user} = \sum_{j=1}^{m} y_j \, l_j \tag{3}$$

The optimization on the mobile users is to purchase the right number of packets (bits) that maximizes its utility, subjected to bit length constraint. The utility is defined as the total QoE gain subtracted by the financial cost paid by the user.

$$U_{user} = a_1 \log\left(a_2 \sum_{j=1}^{m} q_j \, l_j \prod_{k \in \pi_j} (1 - P_k) + a_3\gamma + a_4 \right) - \sum_{j=1}^{m} y_j \, l_j \tag{4}$$

$$s.t.\ U_{user} \geq 0$$

$$l_{min} < l_j < l_{max}$$

where l_{min} and l_{max} represent minimum number of bits to encode the multimedia data and the maximum number of bits that can be supported within a frame.

1.2.2 UTILITY OF PROVIDER-CARRIER ALLIANCE

The content provider and the wireless carrier will negotiate a commission rate for leasing the wireless channel resource, in order to achieve the pledged QoE for the end user. The utility of the provider-carrier alliance U_{PC} could be estimated as the total revenue charged from the mobile user subtracted by the operational cost of provider and the carrier.

$$U_{PC} = \psi_{user} - \psi_{provider} - \psi_{carrier} \tag{5}$$

The payment received from the user ψ_{user} is modeled in equation (3). The operational cost of the provider $\psi_{provider}$ is a function of source coding control as shown in equation (6), where α is the cost per bit of source coding control.

$$\psi_{provider} = \alpha \sum_{j=1}^{m} q_j \, l_j \tag{6}$$

The cost on the wireless carrier side can be modelled as logarithmic function of successful transmission probabilities of the ancestor frames.

$$\psi_{carrier} = \beta \sum_{j=1}^{m} \log \prod_{k \in \pi_j} (1 - P_k) \tag{7}$$

where β denotes the operating cost of the wireless carrier. The optimization problem for the provider-carrier alliance is to set the proper cost per bit of multimedia data that maximizes its utility.

$$U_{PC} = \sum_{j=1}^{m} y_j \, l_j - \alpha \sum_{j=1}^{m} q_j \, l_j - \beta \sum_{j=1}^{m} \log \prod_{k \in \pi_j} (1 - P_k) \tag{8}$$

$$s.t. \; U_{PC} \geq 0$$

1.3 STACKELBERG GAME ANALYSIS

We begin by first normalize the utility equations (4) and (8) to reduce the number of adjustable parameters. Then the utility maximizing problem between the provider-carrier and the user is be modeled as a two stage Stackelberg game to determine the Nash Equilibrium of the game. Nash equilibrium of the game is defined as the set of strategies, one for client and one for the service provider such that both players have no incentive deviating from that strategy [11].

On the end user side, the user controls the number of multimedia frames (bits) to purchase in order to maximize their utility subject to the total multimedia bit constraint $\sum_{j=1}^{m} l_j \leq L$. Optimality can is reached by taking the equality condition as shown below. By choosing a higher value for L, the user can achieve higher multimedia quality at higher financial cost.

$$\sum_{j=1}^{m} l_j = L \tag{9}$$

The per-bit cost y_j for each packet would achieve optimal solution, however, the feasibility of achieving such a global solution would be impractical for a large amount of multimedia packets within a number of user flows. Therefore, instead of finding the Nash Equilibrium per-bit cost y_j for each packet, we can simplify the proposed model to determine the single sub-game perfect Nash Equilibrium base price y_0 that leads to the best utility at provider-carrier alliance side.

We define the normalized base price y_0 as the unit quality gain for each multimedia bit. As shown in Fig. 2, a multimedia frame in a GOP has a dependency on the ancestor frames and the descendent frames to decode their data. The set of frames whose decoding depend upon the successful decoding of packet j, is defined as $\pi_{j'}$. Then the per-bit cost of multimedia packet j can be presented as

$$y_j = y_0 \sum_{k \in \pi_{j'}} q_k \tag{10}$$

The above equations (9) and (10) can be used to simplify the utilities of the user (4) and provider-carrier (8) defined in the previous section.

$$U_{user} = a_1 \log\left(a_2 L \sum_{j=1}^{m} q_j \prod_{k \in \pi_j} (1 - P_k) + a_3 \gamma + a_4 \right) - y_0 L \sum_{k \in \pi_{j'}} q_k \tag{11}$$

$$U_{PC} = y_0 L \sum_{k \in \pi_{j'}} q_k - \alpha L \sum_{j=1}^{m} q_j - \beta \sum_{j=1}^{m} \log \prod_{k \in \pi_j} (1 - P_k) \tag{12}$$

The two-stage game is solved using backward induction. We begin by converting the utility functions into the best response functions and then we look for mutual best response $\{L^*, {y_0}^*\}$. Mutual best response is the set of strategies which produce the most favorable outcome for a player, taking other players' strategies as given [11].

1.3.1 BEST RESPONSE OF THE USER

In stage I, as the leader of the Stackelberg game, the provider-carrier offers a real-time cost for multimedia frames y_0 to the users. In stage II, as a follower in Stage I, the user decides the amount of multimedia data L to purchase based on the offer from provider-carrier. It can be proved that utility of the user for downloading the j^{th} packet is concave for given cost y_0 and $L_{min} < L < L_{max}$ by computing the second order derivative of the utility function.

$$\frac{\partial U_{user}}{\partial L} = \frac{a_1\, a_2 \sum_{j=1}^{m} q_j\ \prod_{k\,\in\,\pi_j}(1-\ P_k\,)}{a_2\, L \sum_{j=1}^{m} q_j\ \prod_{k\,\in\,\pi_j}(1-\ P_k\,) + a_3\gamma + a_4} - y_0 \sum_{k\,\in\,\pi_{j'}} q_k \tag{13}$$

$$\frac{\partial^2 U_{user}}{\partial L^2} = -\frac{a_1\, {a_2}^2 \sum_{j=1}^{m} q_j^2\ \prod_{k\,\in\,\pi_j}(1 - P_k\,)^2}{(a_2\, L \sum_{j=1}^{m} q_j\ \prod_{k\,\in\,\pi_j}(1-\ P_k\,) + a_3\gamma + a_4)^2} \tag{14}$$

Since a_1 is positive system parameters and all the other terms in the equation are squared, we have the second derivative $\frac{\partial^2 U_{user}}{\partial L^2} < 0$. Therefore, the utility function of user is concave and the best response of the user L^* that would maximize their utility can be computed by equating $\frac{\partial U_{user}}{\partial L} = 0$.

$$\frac{a_1\, a_2 \sum_{j=1}^{m} q_j\ \prod_{k\,\in\,\pi_j}(1-\ P_k\,)}{a_2\, L \sum_{j=1}^{m} q_j\ \prod_{k\,\in\,\pi_j}(1-\ P_k\,) + a_3\gamma + a_4} - y_0 \sum_{k\,\in\,\pi_{j'}} q_k = 0 \tag{15}$$

The equation (15) can be solved to derive the fixed relationship between the user's multimedia requirement L and the cost charged by the provider-carrier alliance y_0. Therefore, the user always purchases L^*number of frames based on equation (16) in order to achieve maximum utility.

$$L\,(y_0\,) = \frac{\dfrac{a_1\, a_2 \sum_{j=1}^{m} q_j\ \prod_{k\,\in\,\pi_j}(1-\ P_k\,)}{y_0\ \sum_{k\,\in\,\pi_{j'}} q_k} -\ a_3\gamma - a_4}{a_2\ \sum_{j=1}^{m} q_j\ \prod_{k\,\in\,\pi_j}(1-\ P_k\,)} \tag{16}$$

1.3.2 BEST RESPONSE OF THE PROVIDER-CARRIER ALLIANCE

The carrier-provider being rational knows the amount of multimedia frames the user would purchase L^*, such that their utility is maximized for any given cost y_0. Therefore, the utility of the user shown in equation (12) can be rewritten in terms of y_0 as shown below.

$$U_{PC} = y_0\, L(y_0) \sum_{k \in \pi_{j'}} q_k - \alpha\, L(y_0) \sum_{j=1}^{m} q_j - \beta \sum_{j=1}^{m} \log \prod_{k \in \pi_j} (1 - P_k) \tag{17}$$

It is hard to prove the concavity of the second order derivative of the utility equation. Therefore, we have used Newton method in a way similar to [4] to find the best response $y_0{}^*$.

Lemma 1.1: A real function which is differentiable must be a continuous function [13].

Lemma 1.2: A continuous real function on a closed interval must contain a maximum value and a minimum value [13].

Taking the first derivative of the equations (16) and (17) with respect to y_0 we have

$$\frac{\partial U_{PC}}{\partial y_0} = L(y_0) \sum_{k \in \pi_{j'}} q_k + \frac{\partial L(y_0)}{\partial y_0} \left(y_0 \sum_{k \in \pi_{j'}} q_k - \alpha \sum_{j=1}^{m} q_j \right) \tag{18}$$

$$\frac{\partial L(y_0)}{\partial y_0} = -\frac{a_1}{y_0{}^2\, \sum_{k \in \pi_{j'}} q_k} \tag{19}$$

The equations (18) and (19) shows that the utility function of the provider-carrier alliance is real and differentiable. This combined with Lemma 1, proves that the utility equation is a continuous function.

Since a_1, y_0 and q_k are all positive, the first order derivative of the best response function $\frac{\partial L(y_0)}{\partial y_0} < 0$ at all times. This shows that the function is monotonically decreasing. The multimedia length is constrained as $L_{min} < L < L_{max}$.

$$y_{0_{min}} = \frac{a_1\, a_2 \sum_{j=1}^{m} q_j \; \prod_{k \in \pi_j} (1 - P_k)}{\left[a_2\, L_{max} \sum_{j=1}^{m} q_j \; \prod_{k \in \pi_j} (1 - P_k) + a_3 \gamma + a_4\right] \sum_{k \in \pi_{j'}} q_k} \tag{20}$$

$$y_{0_{max}} = \frac{a_1\, a_2 \sum_{j=1}^{m} q_j \;\; \prod_{k\,\in\,\pi_j}(1 - P_k\,)}{[a_2\, L_{min} \sum_{j=1}^{m} q_j \;\; \prod_{k\,\in\,\pi_j}(1 - P_k\,) + a_3\gamma + a_4] \sum_{k\,\in\,\pi_{j'}} q_k} \tag{21}$$

Therefore, the best response for the base cost y_0 is confined within a close interval $\{y_{0_{min}} < {y_0}^* < y_{0_{max}}\}$. Lemma 1.2 proves the existence of maximum value which can be determined using a generic global searching algorithm.

1.3.3 STACKELBERG EQUILIBRIUM ALGORITHM

Based on the above analysis of the proposed two stage game, we present an iteration based global searching algorithm to implement the smart data pricing scheme. We look for the mutual best response $\{L^*\,, {y_0}^*\}$ that maximizes the utility of both the provider-carrier alliance and the end-user.

Newtons method for Nash Equilibrium

---

1. **Initialization:**
   - 1.1 Initialize the system parameters $a_1,\ a_2,\ a_3$ and a_4.
   - 1.2 set the user preference for given multimedia content γ.
   - 1.3 Define the base cost y_0 and the multimedia quality $q_j\,,\ j \in [1, m]$ and $q_k\,, k \in\ \pi_{j'}$.
   - 1.4 Set the physical channel parameters: length of frame L and packet error rate $P_k\,, k\ \in\ \pi_j$.
2. **Iterations:**
   - 2.1 The algorithms solve for the best responses $\{L^*\,, {y_0}^*\}$. Thereby, determining the utilities of the base station and the client $\{U_{PC}, U_{user}\}$.
   - 2.2 Set the $U_{PC} = U_{user} = L^* = {y_0}^* = 0$.
   - 2.3 Let χ = $y_{0_{min}} : M : y_{0_{max}}$
   - 2.4 **For** i=1: M
     - 2.4.1 Set y_0= χ(i)
     - 2.4.2 Compute the utility of provider-carrier for χ(i):
       $$u_{PC}(y_0) = y_0\, L(y_0) \sum_{k\,\in\,\pi_{j'}} q_k - \alpha\, L(y_0) \sum_{j=1}^{m} q_j - \beta \sum_{j=1}^{m} \log \prod_{k\,\in\,\pi_j} (1 - P_k)$$
     - 2.4.3 **if** $u_{PC}(y_0) > U_{PC}$
       - 2.4.3.1 update $U_{PC} = u_{PC}(y_0)$
       - 2.4.3.2 Set ${y_0}^* = y_0$
       - 2.4.3.3 Calculate the optimal data length
       - 2.4.3.4 Finally determine the utility of the user
         $$U_{user} = a_1 \log\left(a_2\, L \sum_{j=1}^{m} q_j \prod_{k\in\pi_j} (1 - P_k) + a_3\gamma + a_4 \right) - y_0\, L \sum_{k\,\in\,\pi_{j'}} q_k$$
     - 2.4.4 **End if**
   - 2.5 **End for**
3. **Output:**
   The algorithm searches the closed interval space $[y_{0\ min}, y_{0\ max}]$ to determine the Stackelberg game equilibrium $\{L^*\,, {y_0}^*\}$ and the corresponding utilities of base station and client $U_{PC}, U_{user}\}$

Algorithm 1.1 Stackelberg game algorithm using Newtons method.

The computing complexity of the proposed Stackelberg smart media pricing game algorithm is O(M), which comprises of the maximum iteration steps M to determine the optimal value.

Since the best response value for multimedia frame length L^* and the base price ${y_0}^*$, we can make a two-dimensional searching table and update the values in the table during sparse time periods between the multimedia transmission. The computation complexity and the latency between the data transmission can be reduced by determining the mutual best response directly by searching the table whenever the game needs to be performed.

1.4 SIMULATION STUDY

In this section, we evaluate the performance of the proposed QoE- sensitive multimedia pricing framework. The video sequence for simulation is "Foreman" with H.264 coder. The I-frame's successful transmission only relies on itself, while the P-frames refer to the previous I-frame and P-frames. The systems parameters used to fine tune the QoE model a1~ a4 were chosen as 3.8, 4.9, 3.6 and 3.5 respectively based on the large number of subjective video quality tests conducted by K. Yamagishi, et.al [13]. The initial values for α and β are 0.1 and 4 respectively.

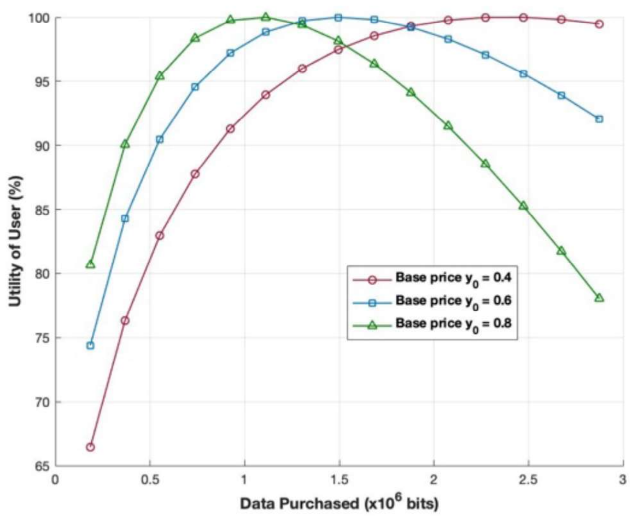

Fig. 1.3. Utility of user versus data purchased for various base price y_0

In the previous section, we have mathematically proved that the utility of the user is concave for any price y_0, declared by the carrier-provider alliance. The Fig. 1.3, shows that the utility of the user versus the amount of data purchased for base price $y_0 = 0.4, 0.5\ and\ 0.6$ repectively. The QoE of the shown in equation (2) user is modeled as a function of user's personal preference. For a fixed base price $y_0 = 0.4$, the value of γ is altered to demonstrate the impact of personal preference on the user's QoE in Fig. 1.4. It can be observed that for low data rates, the impact of γ is significant.

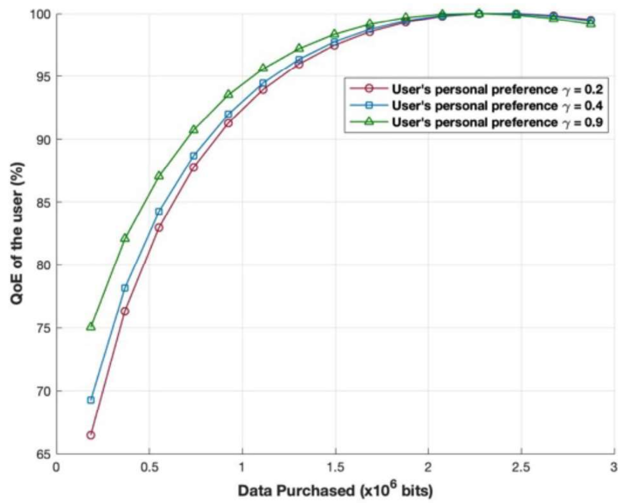

Fig. 1.4. QoE of the user versus data purchased based for various user's personal preference γ.

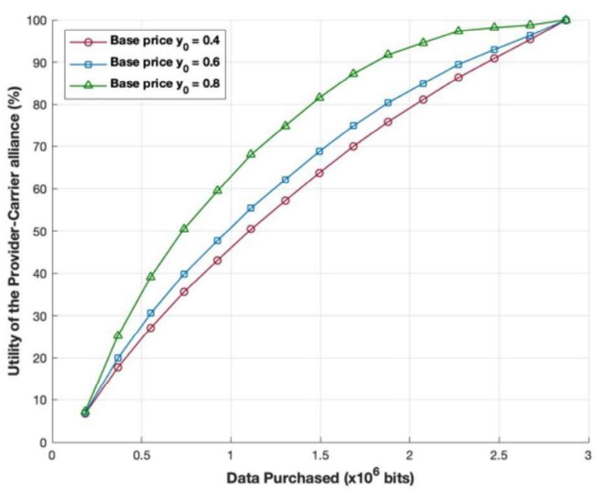

Fig. 1.5. Utility of provider-carrier versus data purchased for various base price y_0

Fig. 1.5 shows the normalized utility of provider-carrier alliance for base price $y_0 = 0.4, 0.5 \; and \; 0.6$ repectively. Fig. 1.6 shows the utility of the provider-carrier when we change the operation cost of the wireless carrier β and content provider α respectively. It can be observed that for a fixed price y_0, the utility decreases linearly with increasing α and β. Therefore, it can be concluded that the different initialization of the constant parameter does not affect the proposed utility equations.

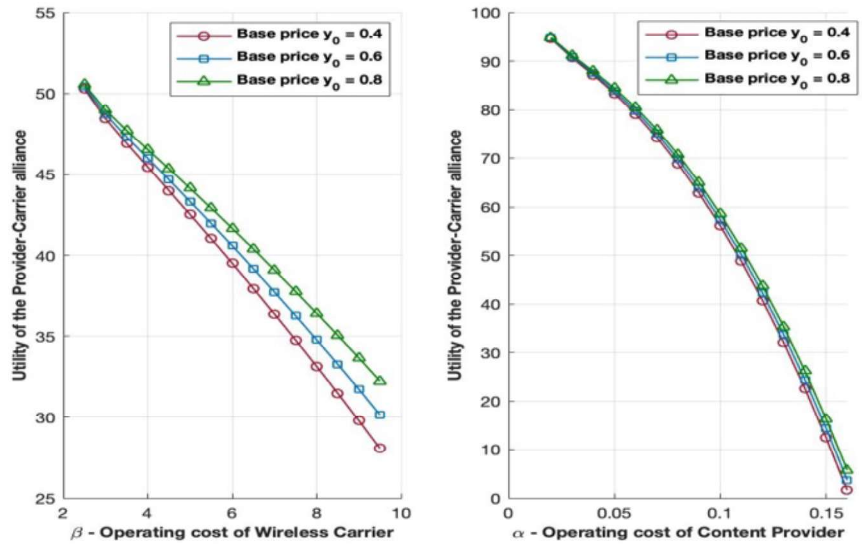

Fig. 1.6. Utility of provider-carrier versus operation cost of the wireless carrier and the service provider

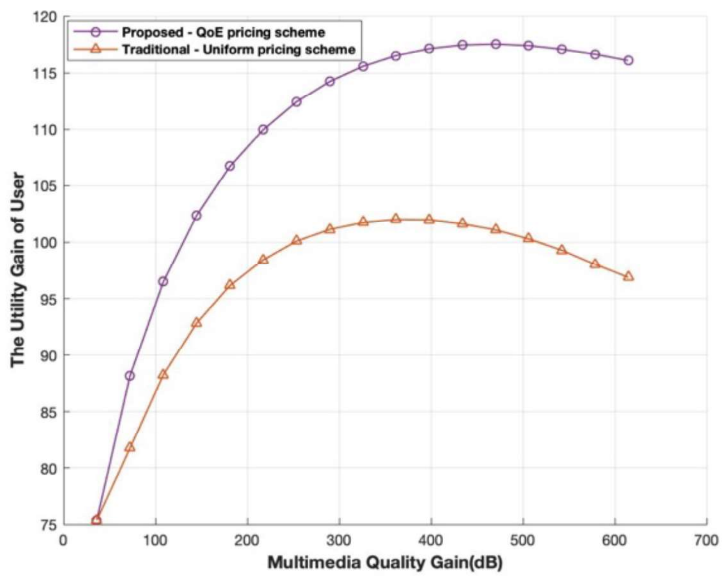

Fig. 1.7. Utility gain of user versus the multimedia quality gain

The proposed QoE-sensitive multimedia pricing scheme allocated different prices to frames based on the packet length and PSNR. We compare our scheme with throughput based traditional pricing scheme based on equal frame importance. In this scheme, each frame uses the same PSNR and bit length i.e. the resource is sold with a fixed price. The utility gain of the user for both these schemes are shown above in Fig. 1.7. It can be observed that our scheme outperforms the uniform pricing scheme significantly. This is because the frames are strategically priced (regular packers are incented with lower price while important packets are granted higher price) using Stackelberg game, so as to enhance the overall QoE of the user.

1.5 CONCLUDING REMARKS

In this research work, we leverage the Smart Media Pricing (SMP) framework and propose a new QoE-sensitive multimedia pricing scheme using Stackelberg game. The contemporary video coding scheme such as H.265 encode video frames with unequal importance. This diversity allows us to price the multimedia frames based on the importance. The interactions between wireless carrier – content provider alliance and the end user were modeled as a two-stage Stackelberg game. We present an iterative algorithm to determine the Nash Equilibrium of the proposed scheme using backward induction method. Simulation results indicate that higher utilities can be achieved by adopting the proposed QoE-sensitive multimedia pricing scheme. In this work, we consider that wireless carrier charges a pre-negotiated commission rate from the content provider to deliver multimedia content to the end user. As for the future work, the interplay between the content provider and wireless carrier can be modeled as a Stackelberg game in a similar way to determine the Nash Equilibrium.

CHAPTER 2: PROSPECT THEORETIC PRICING FOR QOE MODELING IN WIRELESS MULTIMEDIA NETWORKING

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 chapter, 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. Simulation results also indicated that PT-based modeling can improve system throughput and network revenue.

2.1 INTRODUCTION

With multimedia becoming the predominant traffic in wireless communication networks with enormous increase between 2017-2022 [14], 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) [15]. 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) [16] 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. 2.1. 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 2.3. 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.

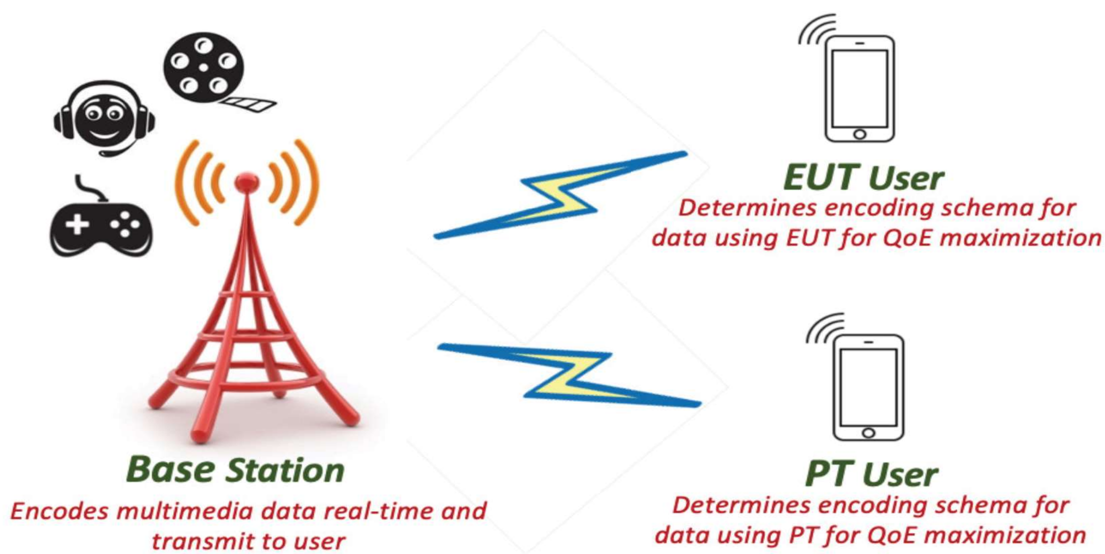

Fig. 2.1. An illustration of QoE driven system model. EUT user versus PT user

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 [17]. 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 2.4.

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 [18], Markov decision process-based network assisted mobile streaming [19], multimedia resource allocation [20] and downlink power level optimization in non-orthogonal multiple access wireless multimedia [21] have been proposed. However, these QoE models do not evaluate user satisfaction from a human psychological point of view.

Last decade has witnessed 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 [22] and [23] 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 [24], we have used dynamic value function to model QoE function of the user.

2.2. 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 [25] 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 [26].

2.2.1 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 2.1 stated below.

Proposition 2.1: 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 $w(\varepsilon) : [0,1] \overset{onto}{\rightarrow} [0,1]$. (c) w and w^{-1} should be continuous.

2.2.2 VALUE FUNCTION

Losses hurt humans more than winning excites 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 2.2.

Proposition 2.2: 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 that for losses.

A typical weight function and value function as prescribed by prospect theory are shown in Fig. 2.2 below.

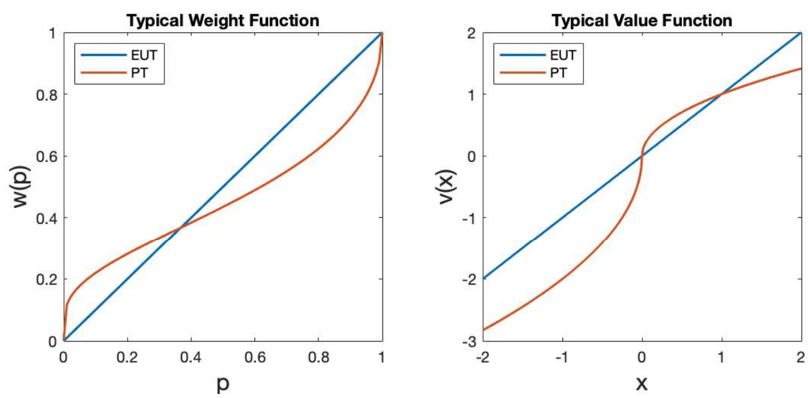

Fig 2.2. Weighting function and value function as prescribed by PT.

2.2.3 REFERENCE POINT DEPENDENCE

The value function captures the human’s 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.

2.3 PT DRIVEN 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.

2.3.1 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 $i = \{1, 2, \dots, N\}$. 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 a 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, [20], and it is given by equation 22 below

$$QoE^{SMP} = log\left(1 + \sum_{i=1}^{N} L_i \left(\alpha\, q_i \prod_{k\, \in \pi_j} (1 - P_k)\, \log\, (1 +\, \beta\, P_{BS}\,)\right)\right) - \sum_{i=1}^{N} L_i\, y_i \qquad (22)$$

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 QoE model will be used by the EUT user in our two-user wireless communication system shown in Fig.2.1.

2.3.2 PROSPECT THEORY BASED QOE DEFINITION

While evaluating the user QoE, people are more sensitive to losses than to gain. In order to capture the loss aversion characteristic among consumers, we have used the asymmetric value function as defined in [25] to model our QoE.

$$v(x) = \begin{cases} x^{\kappa}, & for\ x \geq 0 \\ -\lambda\,(-x)^{\kappa}, & for\ x < 0 \end{cases} \tag{23}$$

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) $\widehat{L_\iota} \geq L^*$, he/she is more satisfied and so the QoE is in gain region. Similarly, if received data $\widehat{L_\iota} < L^*$, due to channel conditions or other technicalities then the QoE is in loss region. In conclusion, L^* is a suitable reference point for our QoE model and the value function can be integrated as shown below.

$$QoE^{PT} = \begin{cases} L^{*QOE^{SMP}}; & \widehat{L_\iota} \geq L^* \\ -\lambda\,(-L^*)^{QOE^{SMP}}; & \widehat{L_\iota} < L^* \end{cases} \tag{24}$$

2.3.3 PROSPECT THEORY DYNAMIC QOE DEFINITION

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 $\widehat{L_\iota} \geq L^*$ 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 by Chia-Han Lee [24]. This QoE model is used for the PT user shown in Fig. 2.1.

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 (25) below. This can be visualized as shown in Fig. 2.3.

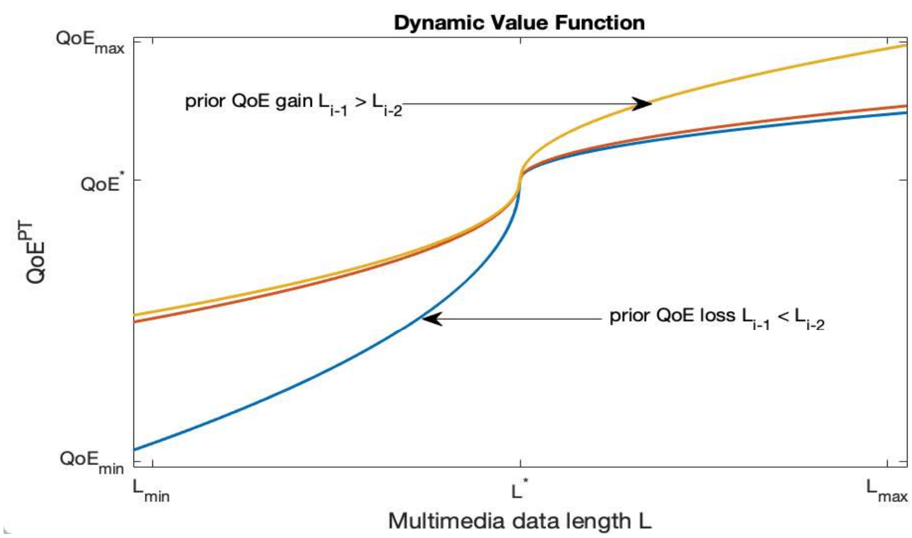

Fig. 2.3. Dynamic value function for QoE modelling

$$QoE^{PT} = \begin{cases} \begin{cases} \mu_1 \, L^{*QOE^{SMP}}; & \widehat{L_i} \geq L^* \\ -\lambda \left(-L^*\right)^{QOE^{SMP}}; & \widehat{L_i} < L^* \end{cases} & \hat{L}_{i-1} > \hat{L}_{i-2} \\ \begin{cases} L^{*QOE^{SMP}}; & \widehat{L_i} \geq L^* \\ -\lambda \left(-L^*\right)^{QOE^{SMP}}; & \widehat{L_i} < L^* \end{cases} & \hat{L}_{i-1} = \hat{L}_{i-2} \\ \begin{cases} L^{*QOE^{SMP}}; & \widehat{L_i} \geq L^* \\ -\lambda \, \mu_2 \left(-L^*\right)^{QOE^{SMP}}; & \widehat{L_i} < L^* \end{cases} & \hat{L}_{i-1} < \hat{L}_{i-2} \end{cases} \tag{25}$$

2.3.4 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 is maximized.

$$\underset{L_i}{maximize} \sum_{i=1}^{M} QoE^{PT} \qquad (26)$$
$$s.t.\ L_{i_{min}} < L_i^* < L_{i_{max}}$$

2.4 MULTIMEDIA QOE MAXIMIZATION SOLUTION

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

2.4.1 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 properly 2.1.

Property 2.1: 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. Since the 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, we can observe that all terms 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.

$$\frac{\partial\ QoE^{SMP}}{\partial L} = \frac{\sum_{i=1}^{n} \alpha\ q_i \prod_{k\ \in \pi_j}(1-P_k)\ \log\ (1+\ \beta\ P_{BS}\ )}{\sum_{i=1}^{n} L_i \left(\alpha\ q_i \prod_{k\ \in \pi_j}(1-P_k) \log\ (1+\ \beta\ P_{BS}\ )\right)+1} - \sum_{i=1}^{n} y_i \tag{27}$$

$$\frac{\partial^2\ QoE^{SMP}}{\partial L^2} = -\frac{\sum_{i=1}^{n} \alpha^2 q_i^2 \prod_{k\ \in \pi_j}(1-P_k)\ \log^2\ (1+\ \beta\ P_{BS}\ )}{\left(\sum_{i=1}^{n} L_i \left(\alpha\ q_i \prod_{k\ \in \pi_j}(1-P_k) \log\ (1+\ \beta\ P_{BS}\ )\right)+1\right)^2} \tag{28}$$

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.

$$L^* = \frac{\sum_{i=1}^{n} \alpha\ q_i \prod_{k\ \in \pi_j}(1-P_k)\ \log\ (1+\ \beta\ P_{BS}\ )\ - y_i}{\sum_{i=1}^{n} y_i \left(\alpha\ q_i \prod_{k\ \in \pi_j}(1-P_k) \log\ (1+\ \beta\ P_{BS}\ )\right)} \tag{29}$$

During implementation, the EUT user will 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.

2.4.2 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 2.1: When the value function follows the postulates of prospect theory prescribed in proposition 2.2, 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 (29) during two subsequent services with QoE_1^{SMP} & QoE_2^{SMP} being the actual value for quality of experience. 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) $QoE_1^{SMP} < QoE_3^{SMP} < QoE_2^{SMP}$ and b) $QoE_1^{SMP} < QoE_2^{SMP} < \overline{QoE}_3^{SMP}$. By using PT value function to compute the user perceived QoE, the $\overline{QoE}_3^{PT}$ is 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 $\sum_{i=1}^{N} L_i^*$ is monotonic.

Now considering the case where the $QoE_1^{PT} < QoE_2^{PT}$. Now for the subsequent interaction function is evaluated with a value function shifted towards gain region. Hence for QoE to be maximized, the value function must remain the gain region $QoE_2^{PT} < QoE_2^{PT}$ and amount of resource purchased should be non-zero. Therefore, function has to be monotonically increasing.

By considering Lemma 2.1 and other constrains for maximizing the QoE for each service, we present an algorithm to determine the optimal multimedia content for the PT user.

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** $\boldsymbol{QoE_{n-1}^{PT} > QoE_{n-2}^{PT}}$**:**
      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** $\boldsymbol{QoE_{n-1}^{PT} < QoE_{n-2}^{PT}}$**:**
      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.

Algorithm 2.1 Prospect theoretic QoE maximization algorithm.

2.5 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 (22) and (25). 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. 2.4., it can be observed that the PT user achieves higher QoE by purchasing lesser data from the base station under same channel characteristics.

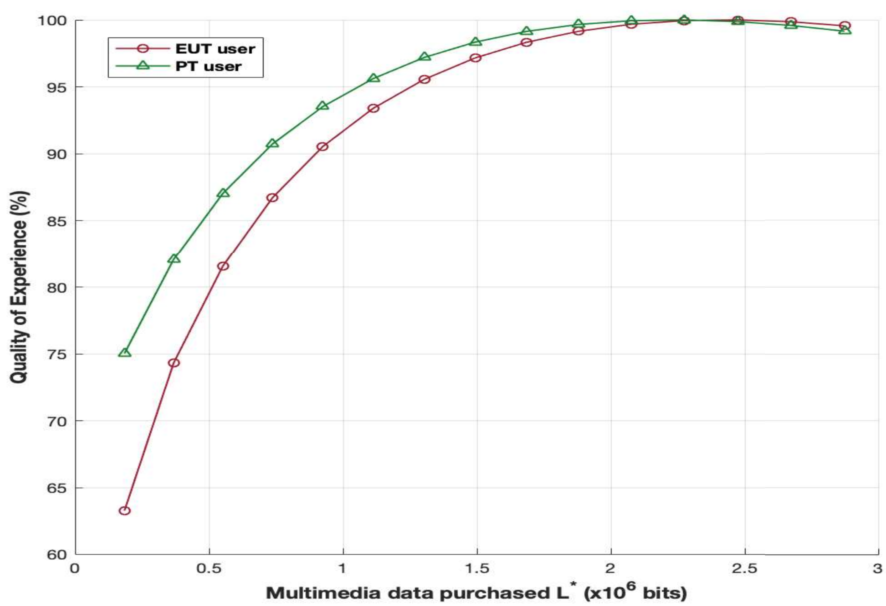

Fig. 2.4. Quality of Experience - EUT user versus PT user

The distortion in human cognition is captured using PT. In order to model the distortion, we have considered two channels in Fig. 2.5. In Fig. 2.5(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 then the EUT user. Therefore, PT based approach works flawlessly in a recovering channel.

In Fig 2.5(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.

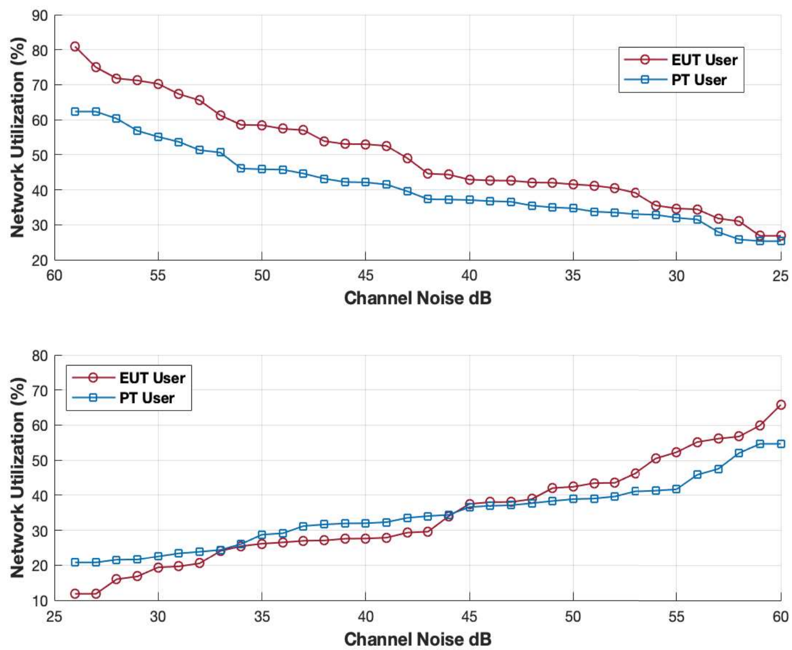

Fig. 2.5. Network utilization against channel noise - EUT user versus PT user

PT user performed significantly better in a recovering channel while EUT user seemed to have an upper hand in a 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 the Fig. 2.6, 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.

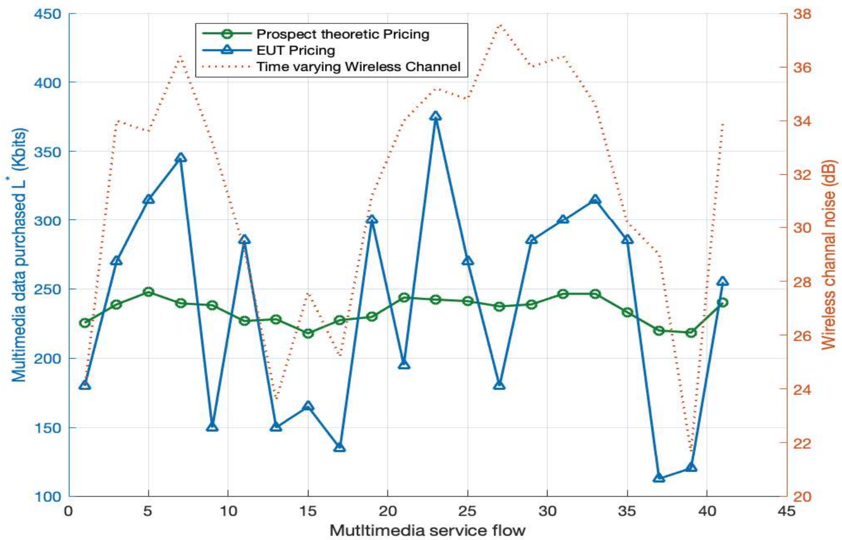

Fig. 2.6. Analysis over a time varying channel - EUT user versus PT user

2.6 CONCLUDING REMARKS

In this research, we have restructured the three-dimensional SMP pricing QoE model from prospect theoretic perspective, taking into account the user psychological effect. The s-shaped asymmetric value function has used to describe the variation of user perceived QoE from its actual value. We then introduce dynamic value function to model subsequent multimedia transactions. A QoE-maximization game between a EUT user and a PT user was investigated to test the competence of proposed model. Simulation results indicate a boost in QoE for the user and significant reduction in network utilization – hinting higher profits for the base station.

As a suitable extension to this work, we would investigate weighting function in PT and explore machine learning techniques such as Generative Adversarial Networks (GAN) to further enhance the QoE models. Another focus of our research is to model the system parameters used in dynamic value function μ_1 and μ_2 based on multimedia content preference and channel characteristics.

CHAPTER 3: FUTURE WORK PLAN NEXT YEAR: QOE-SENSITIVE RESOURCE BLOCK PRICING BASED ON NOMA OR OMA, CONTENT IMPORTANCE, CHANNEL NOISE/INTERFERENCE, AND POWER RESOURCE ALLOCATION.

Building upon the success of the network economics research, resource block pricing has been investigated as a suitable paradigm to improve both multimedia QoE and service provider pricing. A next generation wireless multimedia communication architecture which consists of application-based resource allocation is elaborated in Fig 3.1 below. The challenge for such a resource-block driven architecture is for the service provider to meaningfully distinguish between the available resource block and price them accordingly. The other challenge is to for the end-user device to choose the optimal resource block that would provide the best value for the money spend. A systematic approach for application driven resource block pricing and selection are still open challenges.

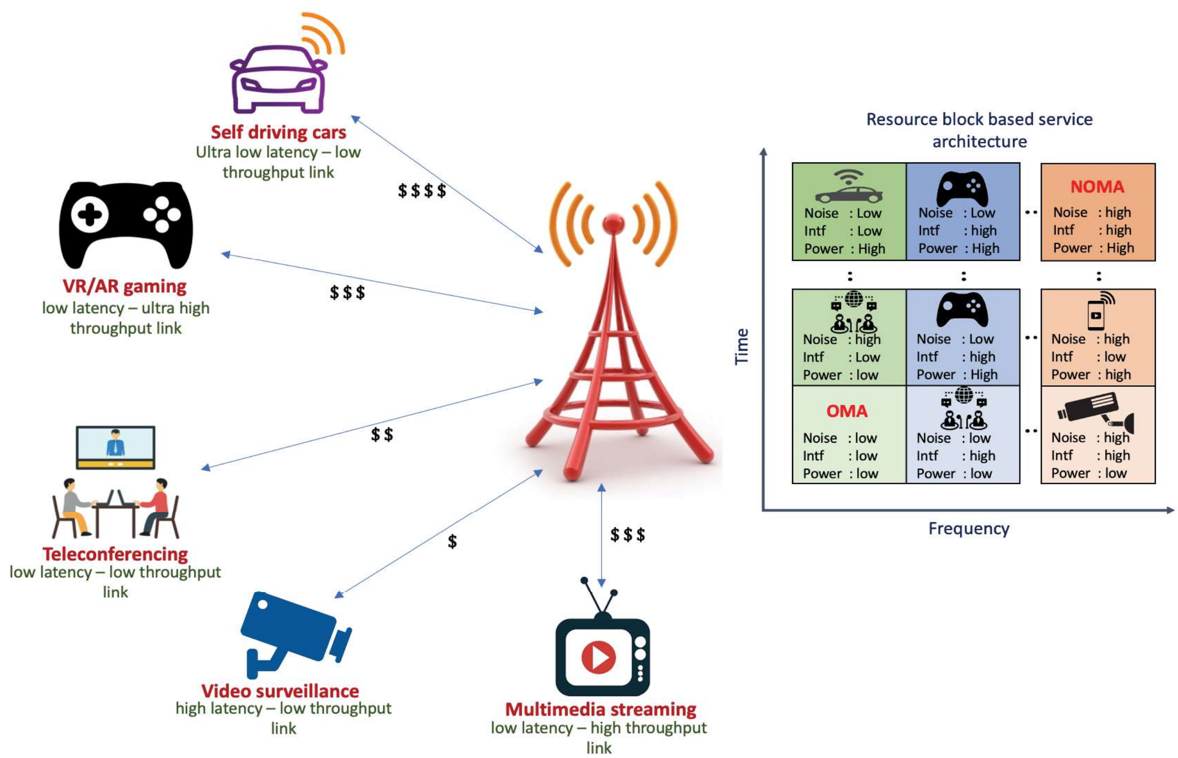

Fig. 3.1. Next generation wireless communication architecture: Application based resource block allocation and non-uniform pricing

3.1 PROPOSED RESOURCE BLOCK PRICING MODEL

The primary objective of this design is for the pricing model to be "content-centric", being aware of the importance of multimedia data carried within a specific resource block. Intuitively, if a user knows the multimedia content carried in a certain resource block is important to QoE, this user could be willing to pay higher price to ensure higher SINR in communication. On the other hand, if a user has paid higher price to ensure higher QoE of its multimedia contents, the base station needs to allocate more communication resource (e.g., power, retransmission, channel coding redundancy, etc.) to that resource block.

In this research, we are trying to determine the equilibrium between the price paid by the user and power allocated by the base station in each of the research blocks. For each of the resource block the user QoE and the base station utility is evaluated using repeated game theoretic model. The user then chooses one of the resource blocks that yields the highest utility. Irrespective of the block chosen by the end user, the utilities of the user and base station are in Nash Equilibrium.

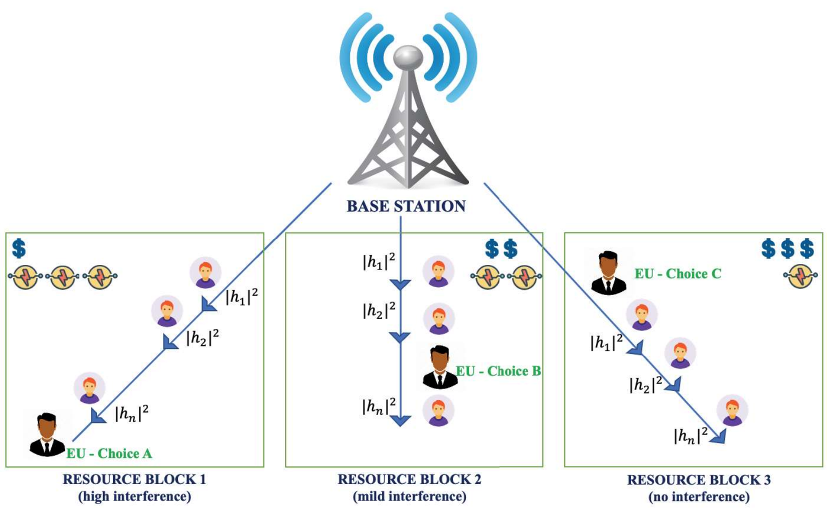

Fig. 3.2. Block pricing system model

We just started exploring this idea, and the exploration is still in progress. We plan to continue working on this topic next year, and we expect to have more research results to report in future.

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