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Novel Pricing Strategies to Improve Quality of Experience in Non-Orthogonal Multiple Access Wireless Communication Networks

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Novel Pricing Strategies to Improve Quality of Experience in Non-Orthogonal Multiple Access Wireless Communication Networks

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Computational Science

by

Krishna Murthy Kattiyan Ramamoorthy

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2023

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IEEE Global Communications Conference (GLOBECOM)

ABSTRACT OF THE DISSERTATION

Novel Pricing Strategies to Improve Quality of Experience in Non-Orthogonal Multiple Access Wireless Communication Networks

By

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Doctor of Philosophy in Computational Science

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Professor Wei Wang (SDSU), Chair

Orthogonal Multiple Access (OMA) has been the predominant mobile network access scheme during the past decade. OMA ensures that the signals of all users are orthogonal to one another across time and/or frequency. Limitation on the number of orthogonal signals and exponential increase in new users, have made Non-Orthogonal Multiple Access (NOMA) as a suitable network access technique for 6G and beyond. Quality of Experience (QoE) and Quality of Service (QoS) are empirical measurements of the service provided to the user by any mobile communication schemes. The ensemble of content-rich services provided through wireless networks have varying QoE specifications. Therefore, it becomes increasingly difficult to develop a step-by-step standardization to quantify the user satisfaction.

This issue is addressed by developing a novel economic approach to meet the QoE demands of the customers in NOMA networks. In the preliminary study, a new pricing framework called Smart Media Pricing (SMP) was developed to price the customer based on the quality of multimedia data purchased. The study proved to be successful and results indicated a significant QoE boost. The study was then extended to NOMA networks. We first developed a new pricing scheme for NOMA called NOMAPricing (NOMAP). Game-theoretic methods were leveraged to show that the NOMAP framework benefits both the service provider and the mobile customer. The short-comings of measuring the user QoE using Expected Utility

Theory (EUT) were then addressed by adopting postulates from prospect theory.

In NOMA, the service provider superimposes the data of all users and transmits them simultaneously. The user devices segregate their content from the amalgamated signal and discards the rest. In a device-to-device (D2D) communication enabled NOMA network, the user can retransmit the data of other customers before discarding them. NOMAP model was ameliorated with conjunction of auction-theoretic solutions to incentivize and promote data relaying. Finally, although NOMA has several merits than the de-facto standard OMA, the switch from OMA to NOMA would be phased out. NOMAP model was tweaked as Orthogonal-Centric Pricing (OCP) to improve customer QoE in a NOMO-OMA hybrid network. The model also promotes users to shift data from OMA to NOMA to offload the service providers.

In this dissertation, we present the utility definitions for the above mentioned models. Optimization solutions for the models derived from game theory, prospect theory, and auction theory are discussed and implementation references are provided. Numerical simulations were also carried out and the results showcase the merits of QoE based pricing models for next-generation mobile networks.

Chapter 1

Introduction

1.1 Wireless networks - 6G and beyond

Wireless networks and mobile communications have become the growth-driving factor among several sectors like finance, transport, retails, and health. The increasing demand for automation and unified device-to-device (D2D) connectivity have been pushing the boundaries of wireless networks and it has become one of the fast-evolving and rapidly advancing technologies. The global wireless connectivity market is projected to grow 10,000-folds to grow to USD 141.1 billion market by 2025.

The explosive boom in the mobile users, internet-ready devices and content-rich applications have made network bandwidth a very valuable resource. Allocation of time and bandwidth to connected devices are two fundamental resource allocation problems in a wireless communication channel. With thousands of new devices getting mobile connectivity every-day, it becomes challenging to fairly allocate the available resources among the users. Therefore, it becomes important to introduce efficient network resource allotment and management protocols.

The key technology that enables the differentiation of various generations of wireless systems is the multiple access scheme. The first generation (1G) introduced Frequency Division Multiple Access (FDMA) as the network access scheme. Time Division Multiple Access (TDMA) and Code Division Multiple Access (CDMA) were used in the subsequent generations (2G and 3G) of mobile communication. Orthogonal Frequency Division Multiple Access (OFDMA) has been the preferred method of resource allotment since the launch of 4G technology. To prevent or reduce interference between devices, orthogonal resources are utilized either in frequency, code or time domain in all the above mentioned schemes.

In order to achieve higher connectivity and improved spectral productivity, Non-Orthogonal Multiple Access (NOMA) is proposed [10] for the upcoming generations of mobile communications. In NOMA, the signals transmitted to users are non-orthogonal and so they mix with one another. NOMA keeps the interference manageable while keeping the increase in receiver complexity within acceptable limits. One of the major challenges in NOMA implementation is meaningful power allocation for perfect signal recovery, while improving the Quality of Experience/Service (QoE/QoS) delivered.

1.2 QoE/QoS based pricing models

Providing satisfactory QoS amidst the ever-increasing wireless service demand is a major topic of research in network economics. Scientists are investigating various innovative pricing strategies that depend on user QoS with a goal to maximizing both service provider earnings and user welfare. A recent study [11] suggested a dynamic and fair pricing strategy where the amount of data provided and the level of QoS achieved were accounted for by charging a customer. This approach is unique in a way where the customers can still request for certain levels of quantity and quality but they only pay for the level of quantity and quality that is actually delivered [11]. This provides with a greater advantage during traffic/congestion. Another study proposed the QUEST, which is a “QoS-aware dynamic cost management” scheme, that determined the ideal strategy for pricing in the sensor-cloud market [12].

Scientists have also applied QoS-based pricing schemes for call services based on received signal strength indicator (RSSI) [13] and call services that can be used for eSIM [14]. Also, a comprehensive study by [15] categorized users based on their service requirements and designed pricing schemes for all possible QoS levels that are applicable to massive IoT scenarios. In this dissertation, we adopt a similar course of action to the charge the QoE/QoS delivered in a NOMA enabled mobile network.

1.3 Dissertation contributions and organization

This dissertation jointly addresses the QoE challenges in wireless networks and profit maximization problem of the service providers. Several pricing strategies have been proposed, mathematically modelled and numerically analyzed.

Chapter 2 highlights the findings from our preliminary study. The video coding scheme HEVC H.265 breaks down the videos into I, P and B frames or group of packets (GOP). I GOPs are non-dependent frames and have high quality contribution to a video. P GOPs are mid-tier frames with dependence on I frames and B GOPs have dependency on both directions with minimum quality contribution. Any multimedia data can be coded with varying number of I, P and B frames. In this chapter, a smart media pricing framework has been proposed to price the I, P and B GOPs differently. The results from the chapter show a considerable QoE boost for the customer and a increase in network profits.

Owing to the success of smart media pricing model, QoE based pricing was adapted to NOMA enabled mobile networks. In **Chapter 3** NOMA Pricing (NOMAP) model is presented. NOMAP aims to jointly maximize the QoE of the customers and revenue of the service providers. The interaction between both the different parties were studied using game-theoretic methods and methodology to obtain the optimal solution has been presented.

Prospect Theory (PT) [16] presents solutions to the problems in modelling user satisfaction or human cognition using Expected Utility Theorem (EUT). In **Chapter 4**, the postulates from PT were adopted to to built a human cognition aware QoE pricing model for NOMA network.

In a NOMA network, the signals transmitted to the users are non-orthogonal. Therefore, every user in the network receive signals belonging to other users. By enabling Device-to-Device communication within NOMA network, the users can cache data of other users and retransmit them to further improve the QoE. First and second price auction techniques were studied to draft an incentive model to promote D2D communication. The implementation details are presented in **Chapter 5**.

NOMAP model was also adapted for a hybrid network with support for both OMA and NOMA communications. In addition to boosting user QoE, the orthogonality centric pricing model, also provided incentive to the users to shift some of the data from OMA links to NOMA links. This further improved the spectral efficiency of the network and service provider profits. **Chapter 6** presents the studies carried out on a hybrid NOMA-OMA network.

Finally in **Chapter 7**, conclusions are provided and future research potentials are discussed. The key ideas from our next study on block-chain modelling for NOMA and intelligent reflection surfaces for NOMA are presented.

Chapter 2

Smart Media Pricing

2.1 Background

A rising challenge for content providers and wireless carriers is providing satisfactory Quality of Experience (QoE) to mobile users. This is because wireless multimedia communication technologies continue to advance and end-user experience expectations continue to rise. In our study, a new QoE aware video frames pricing model that allots price determined by the degree of quality contribution as an alternative to typical frame size is proposed. The utility maximization interactions among the wireless carrier, the service provider and the customer were formulated and analysed. The backward induction technique was employed to solve this problem. This method converted the problem into Stackelberg game-theoretic model to obtained optimal solution. The results from simulations showed that where the Stackelberg equilibrium exists securely, all three entities can obtain best utility. Numerical analysis were carried out and the results illustrate that merits of deploying QoE based pricing scheme.

The materials presented in Chapter 2 have been presented at the 2019 IEEE Global Communications Conference (GLOBECOM) [2].

2.2 Introduction

The global IP traffic is expected to increase almost three-folds from the years 2017 - 2022 based on forecast information from Visual Networking Index (VNI) by Cisco. Mixed, augmented and virtual reality transmissions are predicted to increase by 12 times globally, with a 65% average annual growth rate over the specified period of time [17]. This implies that there will be an exponential increase in video traffic leading to higher QoE expectations from mobile users. This in turn will lead to satisfying QoE requirements becoming the primary distress for content providers due to bandwidth limitations. If not satisfied, there will be decreased usage of applications/services and, ultimately, lower earnings [18].

In multimedia communications, digital video compression methods have been widely utilized. The current updated standard in digital video compression is nothing but H.265 or HEVC. The principle behind HEVC is dividing the video into Group of Pictures (GOP), and then encoding it. Video stream is made of bi-directional dependent B, forward-dependent P and independent I frames [19]. Thus, the video packets have different levels of importance and these frames require varying energy consumption and communication bandwidth [20].

For video services, a novel method called Smart Media Pricing (SMP) that prices QoE instead of binary data traffic has been proposed. Philosophy of the SMP is to set the price of the video frames depending on the quality contribution. [21].

Figure 2.1 [2] shows a common model for economic video services in wireless communication. The user with certain QoE demands request for video content from the service provider. In order to fulfil transmission of the requested content, the provider rents a channel from wireless carriers. By assigning resources to the user, the carrier guarantees that the video transmitted attains the desired level of QoE. In this chapter, a decision-making method built on Stackelberg game theory is developed. This method balances the money paid by the mobile user with the quality of video.

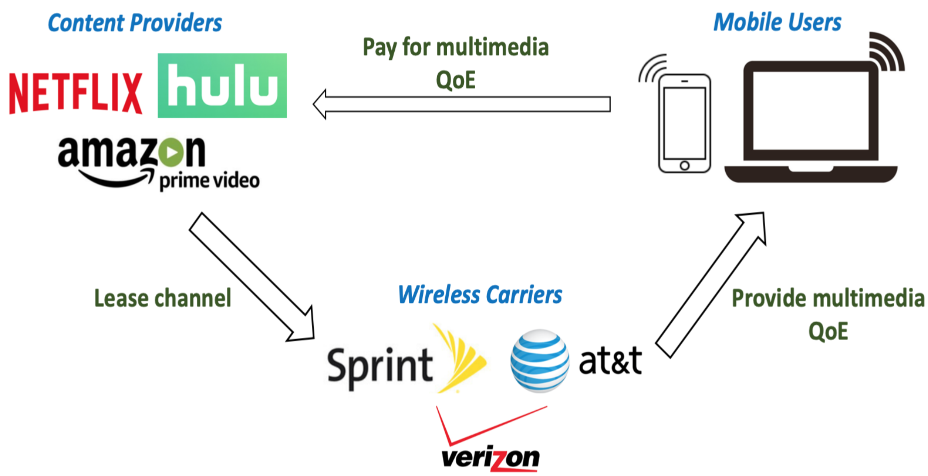

Figure 2.1: Three party interaction: Provider, Carrier and User.

In order to improve revenue, content providers around the world have rapidly changed their pricing strategies. Most of them are moving away from flat-rate pricing [22]. On the other hand, studies have proposed various pricing concepts to mitigate network congestion issues and improve profit maximization. Several pricing concepts have been proposed in the literature, including expected capacity pricing, edge pricing, smart-market pricing, Paris-Metro pricing, responsive pricing, and bandwidth effective pricing [22]. A disadvantage of these pricing methods is that they do not consider important factors such as achievable quality gain under similar channel conditions and user preferences for video content.

Smart media pricing has been a topic of inquiry by some researchers [20] as it allocates pricing based on reducing video distortion, and device to device relay communication, which encourages devices to participate in content forwarding [23]. The service model between the carrier, provider, and end users have also been studied using a game theoretic methods for non-concave function [24].

2.3 Smart Media Pricing (SMP) model

Figure 2.1 [2] displays a three-party interaction that is simplified into a dual player game by combining the carrier and provider into a single entity. Typically, both the combined parties would negotiate privately and form this alliance, so this paper does not delve into the interaction between them. Figure 2.2 [2] depicts the business model between the dual party alliance and the mobile consumer. In the proposed model, the base station vigorously determines the single bit cost (y_j) for transmitted the video requested by the consumer. As each H.264 video GOPs has varying degrees of quality contribution, the consumer has the freedom to choose the type of bits (y_j) to purchase at a given cost.

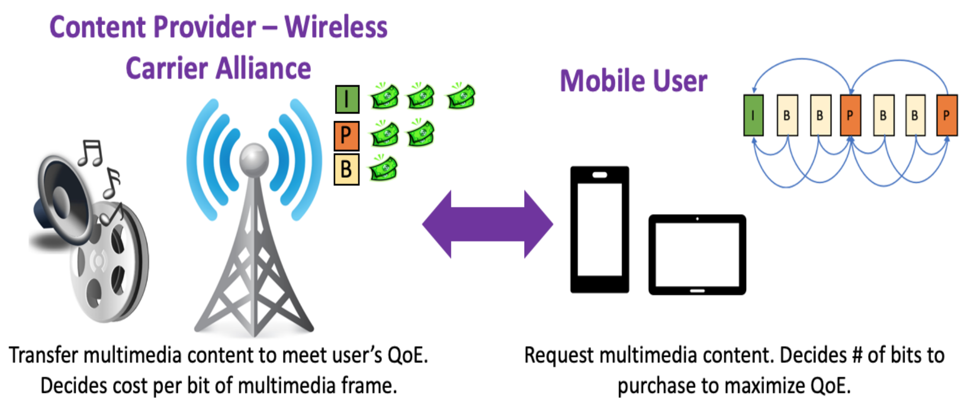

Figure 2.2: SMP: QoE centric wireless communications.

The number of bits bought by the user determines the quality of video experience. Figure 2.2 [2] highlights the link among the three types of frames. When the cost of purchasing bits is low (y_j), the user is inclined to buy a lot of I frames, in comparison at a higher cost, the user aims to reduce the I frames and replace it with P and B frames instead.

2.3.1 User's utility definition

The wireless channel provided by their carrier is used by the mobile user to request a set of frames, identified as $j = 1, 2, ..., m$, from the the seller alliance. The QoE can be determined by assessing the videos content's quality, which can be evaluated through metrics such as the Packet Error Rate (PER) and the Peak Signal to Noise Ratio (PSNR). By dividing the total number of received packets into the number of error packets after implementing forward error correction, the Packet Error Rate (PER) can be determined as shown in the equation below.

$$P_k = 1 - (1 - BER)^{l_k} \tag{2.1}$$

The j^{th} frame's video quality and bit length are respectively represented as q_j and l_j. The set of previously transmitted packet groups that the current frame refers to is denoted by π_j. In order to determine the quality contribution of each frame, its quality contribution, size in bits, and the probability of successful transmission of its dependent frames are taken into account. A log function that describes this relationship is outlined in [25].

$$QoE = c_1 \log \left(c_2 \sum_{j=1}^{m} q_j l_j \prod_{k \in \pi_j} (1 - P_k) + c_3 \gamma + c_4 \right) \tag{2.2}$$

To make the QoE model adaptable, positive system parameters c_1, c_2, c_3, and c_4, are integrated. The customers personal likeness of a specific video is represented by a positive parameter γ. For instance, users who enjoy soccer videos may assign a higher γ, while others who are less interested in soccer can have a lower γ.

To obtain a satisfactory QoE, the customer is required to pay the base station a specific amount, denoted by ψ_{user}. This payment is calculated using the transmission cost per bit of data, represented as y_j, and the total number of video bits requested, represented as l_j.

$$\psi_{user} = \sum_{j=1}^{m} y_j l_j \tag{2.3}$$

Mobile users aim to maximize their utility by optimizing the purchase of packets while ensuring compliance with the bit length limit. To determine the user utility, the financial cost borne by the user is subtracted from the overall increase in QoE. The utility definition is presented as equation (2.4) [2].

$$U_{user} = a_1 \log \left(a_2 \sum_{j=1}^{m} q_j l_j \prod_{k \in \pi_j} (1 - P_k) + a_3 \gamma + a_4 \right) - \sum_{j=1}^{m} y_j l_j \tag{2.4}$$

$$st.\ U_{user} \geq 0 \quad and \quad l_{min} < l_j < l_{max}$$

Here, l_{min} and l_{max} represent the bits needed to encode the requested video and the bits supported by the transmission link from the base station.

2.3.2 Carrier-provider utility definition

The providers with video content will negotiate with carriers like ATNT and Verizon and agree upon a premium cost to rent the channel. The carriers guarantee to deliver the data to the customer with a promised QoE. Utility definition of this partnership between the provider and carrier, represented by U_{PC}, can be evaluated by subtracting the operational expenses of both parties from the total revenue generated from the mobile user.

$$U_{PC} = \psi_{user} - \psi_{provider} - \psi_{carrier} \tag{2.5}$$

The payment made by the user to the content provider is represented by Equation (2.3). Conversely, the provider's expenditure, denoted as $\psi_{provider}$, is determined by the cost per bit of regulating the code of source.

$$\psi_{provider} = \alpha \sum_{j=1}^{m} q_j l_j \tag{2.6}$$

where the parameter α represents this cost. The money spent by the carrier can be written as a log function of the successful transmission probabilities of the previously transmitted dependent packets.

$$\psi_{carrier} = \beta \sum_{j=1}^{m} \log \prod_{k \in \pi_j} (1 - P_k) \tag{2.7}$$

The aim of the collaboration between the carrier and provider is to determine the optimal cost that maximizes their joint utility, while also factoring in the parameter β, which represents the operational cost of the wireless carrier. The utility definition is presented as Equation (2.8) [2].

$$U_{PC} = \sum_{j=1}^{m} y_j l_j - \alpha \sum_{j=1}^{m} q_j l_j - \beta \sum_{j=1}^{m} \log \prod_{k \in \pi_j} (1 - P_k) \tag{2.8}$$

$$st.\ U_{PC} \geq 0$$

2.4 Game-theoretic solution - Stackelberg game

The utility equations (2.4) and (2.8) are initially normalized to reduce the unknowns. Subsequently, the problem of maximizing utility is modeled as a Stackelberg game between the seller and the buyer, aimed at determining the Nash Equilibrium of the game. The Nash Equilibrium refers to a set of strategies, one for the buyer and the other for the seller, in such a way that neither player has a motive to deviate from their respective strategies [25].

The customer has the ability to regulate the data they wish to buy to depending on QoE demand while adhering to the total data constraint of $\sum_{j=1}^{m} l_j \leq L$. The optimal conditions is achieved by satisfying the equality constraint as described below. If the user chooses a higher value of L (i.e., cost), then they can achieve better quality.

$$\sum_{j=1}^{m} l_j = L \tag{2.9}$$

Finding the optimal solution for the price y_j of numerous video packets across several user flows can be a complex task. As a result, rather than finding the optimal price y_j, the proposed model simplifies the process by identifying a base price y_0. The normalized base price y_0 is defined as the unit quality gain for each video bit, as shown in Figure 2.2. The decoding of a video frame in a GOP is determined by its ancestor and descendant frames. The set of frames that rely on the decoding of frame j is represented by $\pi_{j'}$. Thus, the price of video frame j can be expressed as follows:

$$y_j = y_0 \sum_{k \in \pi_{j'}} q_k \tag{2.10}$$

The above equations (2.9) and (2.10) are used to reduce the equations of the consumer (2.4) and the seller (2.8). The simplifications are shown below as equations (2.11) and (2.12) [2].

$$U_{user} = a_1 \log\left(a_2 L \sum_{j=1}^{m} q_j \prod_{k\in\pi_j} (1-P_k) + a_3\gamma + a_4\right) - y_0 L \sum_{k\in\pi_{j'}} q_k \tag{2.11}$$

$$U_{PC} = y_0 L \sum_{k\in\pi_{j'}} q_k - \alpha L \sum_{j=1}^{m} q_j - \beta \sum_{j=1}^{m} \log \prod_{k\in\pi_j} (1-P_k) \tag{2.12}$$

The solution to the game-theoretic problem involves backward induction. First, the utility definitions are translated to best response equations and then the optimal strategy is determined denoted as $\{L^*, y_0^*\}$.

2.4.1 Strategy for the user

During initial round of the Stackelberg game, the seller, who acts as a leader of the game, proposes a price y_0 for video frames to the buyer. In the subsequent round, the user, who acts as the follower, decides the quantity of video data L to buy. The concavity of the user's utility function for downloading the j^{th} packet can be proved by calculating the second-order derivative of the utility equation, given a fixed cost y_0 and with $L_{min} < L < L_{max}$ [26].

$$\begin{aligned}\frac{\partial U_{user}}{\partial L} = &\frac{a_1 a_2 \sum_{j=1}^{m} q_j \prod_{k\in\pi_j}(1-P_k)}{a_2 L \sum_{j=1}^{m} q_j \prod_{k\in\pi_j}(1-P_k) + a_3\gamma + a_4} \\ &-y_0 \sum_{k\in\pi_{j'}} q_k\end{aligned} \tag{2.13}$$

$$\frac{\partial^2 U_{user}}{\partial L^2} = -\frac{a_1 a_2^2 \sum_{j=1}^{m} q_j^2 \prod_{k\in\pi_j} \left(1 - P_k\right)^2}{\left(a_2 L \sum_{j=1}^{m} q_j \prod_{k\in\pi_j} \left(1 - P_k\right) + a_3\gamma + a_4\right)^2} \tag{2.14}$$

Since a_1 is a positive fine-tuning variable and every other variable in the given equation is raised to a power of two, the second order derivative $\frac{\partial^2 U_{user}}{\partial L^2}$ will always be negative. Therefore the buyer's utility equations will always be concave. Thus, the strategy L^* that maximizes the user's utility is computed by setting the first order derivative $\frac{\partial U_{user}}{\partial L}$ to zero [2].

$$\frac{a_1 a_2 \sum_{j=1}^{m} q_j \prod_{k\in\pi_j} \left(1 - P_k\right)}{a_2 L \sum_{j=1}^{m} q_j \prod_{k\in\pi_j} \left(1 - P_k\right) + a_3\gamma + a_4} - y_0 \sum_{k\in\pi'_j} q_k = 0 \tag{2.15}$$

By solving Equation (2.15), a deterministic relationship between the user's video demand L and money quoted by the buyer y_0 can be obtained. Consequently, the user can use Equation (2.16) to determine the optimal number of frames, denoted as L^*, that provides the best return for the investment.

$$L\left(y_0\right) = \frac{\frac{a_1 a_2 \sum_{j=1}^{m} q_j}{y_0 \sum_{k\in\pi'_j} q_k} - a_3\gamma - a_4}{a_2 \sum_{j=1}^{m} q_j \prod_{k\in\pi_j} \left(1 - P_k\right)} \tag{2.16}$$

2.4.2 Strategy for the provider-carrier

The provider-carrier and user act rationally by strategically considering the optimal values of video frames and their costs. The user decides to purchase a particular number of video frames L^* that maximizes their utility function with a given cost y_0. Therefore, we can represent the user's utility function (Equation (2.12)) in terms of y_0 as shown below [2].

$$U_{PC} = y_0 L\left(y_0\right) \sum_{k \in \pi_{j'}} q_k - \alpha L\left(y_0\right) \sum_{j=1}^{m} q_j - \beta \sum_{j=1}^{m} \log \prod_{\kappa \in \pi_j} \left(1 - P_k\right) \tag{2.17}$$

Due to the complexity of calculating the second-order derivative of the equation above, it is difficult to show that the function is concave. Therefore, the Newton's method has been leveraged to obtain the optimal response ${y_0}^*$, following the approach used in [27]. To facilitate this method, the following two lemmas were used [2].

Lemma 1: A function that is differentiable is necessarily a continuous function.

Lemma 2: Every real-valued continuous function defined on a closed interval is guaranteed to have both a minimum and a maximum value within that interval.

$$\frac{\partial U_{PC}}{\partial y_0} = L\left(y_0\right) \sum_{k \in \pi_{j'}} q_k + \frac{\partial L\left(y_0\right)}{\partial y_0} \left(y_0 \sum_{k \in \pi_{j'}} q_k - \alpha \sum_{j=1}^{m} q_j \right) \tag{2.18}$$

$$\frac{\partial L\left(y_0\right)}{\partial y_0} = -\frac{a_1}{y_0^2 \sum_{k \in \pi_{j'}} q_k} \tag{2.19}$$

By differentiating equations (2.16) and (2.17) with respect to y_0, we observe that the provider-carrier's utility function is both real and differentiable, which can be expressed as equations (2.18) and (2.19). The continuity of the utility function can be proved using Lemma 1 and this implies that the function is continuous.

Given that q_k, y_0, and a_1 are all non-zero positive variables, the first-order derivative of the best response function with respect to y_0 is negative. This indicates that the function decreases monotonically. Furthermore, it should be noted that the video length is restricted to values within the range of $L_{\min} < L < L_{\max}$. Therefore, the optimal solution can be determined using an iteration-based global search algorithm as shown as Algorithm 1 [2].

Algorithm 1 Computation of Nash equilibrium solution for SMP model

1. **Initialization:**
    - 1.1. Set up or specify the initial values for the system parameters - a_1, a_2, a_3 and a_4.
    - 1.2. Initialize user preference of given video $\gamma \in [0, 1]$.
    - 1.3. Set the base price y_0 and video quality q_j, $j \in [1, m]$ and q_k, $k \in {\pi_j}'$.
    - 1.4. Initialize wireless channel constrains: length of frame L and PER P_k, $k \in \pi_j$.
2. **Iterations:**
    - 2.1. Algorithm determines for the mutual best strategies $\{L^*, {y_0}^*\}$. This can be used to compute the overall utility of seller and buyer $\{U_{PC}, U_{user}\}$.
    - 2.2. Set the $U_{PC} = U_{user} = L^* = {y_0}^* = 0$.
    - 2.3. Set $\chi = y_{0\ min} : M : y_{0max}$
    - 2.4. **For** i=1: M
    - 2.5. Let $y_0 = \chi$(i)
    - 2.6. Determine the probable utility for provider-carrier $U_{PC}(y_0)$ according to Equation (17)
    - 2.7. **if** $U_{PC}(y_0) > U_{PC}$
        - 2.7.1 Update $U_{PC} = U_{PC}(y_0)$
        - 2.7.2 Set ${y_0}^* = y_0$
        - 2.7.3 Determine the ideal frame length for purchase using Equation (16)
        - 2.7.4 Calculate the value of U_{user} based of Equation (11)
    - 2.8. End **if**
    - 2.9. End **for**
3. **Output:** The program examines the range of the closed interval, $[y_0min, y0max]$, and identifies the Nash equilibrium as $L^*, y0^*$. The respective utilities associated with this equilibrium are U_{PC}, U_{user}.

The aim of the algorithm is to determine optimal values of both the price and video packet length for the seller and buyer. Computing complexity of the algorithm has a $O(M)$. The obtained values can be used to create a two-dimensional search table that can be updated during sparse time periods between video transmissions. This approach can help reduce the complexity and latency between data transmissions by directly determining the Nash Equilibrium through the search table.

2.5 Numerical study

The performance of the SMP pricing method for video content is evaluated, taking into account the QoE. For the simulations, the "Foreman" video sequence, encoded in the H.265 standard was utilized. The QoE model was fine-tuned by setting the values of the parameters $a1$ to $a4$ to 3.7, 4.8, 3.5, and 3.4, respectively, based on numerous subjective video quality tests previously conducted [28]. Error rate of the channel was set at 1e-6, and maximum number of iteration steps, denoted as M, was set to 200. Other cost parameters α and β were set to 0.1 and 4, respectively.

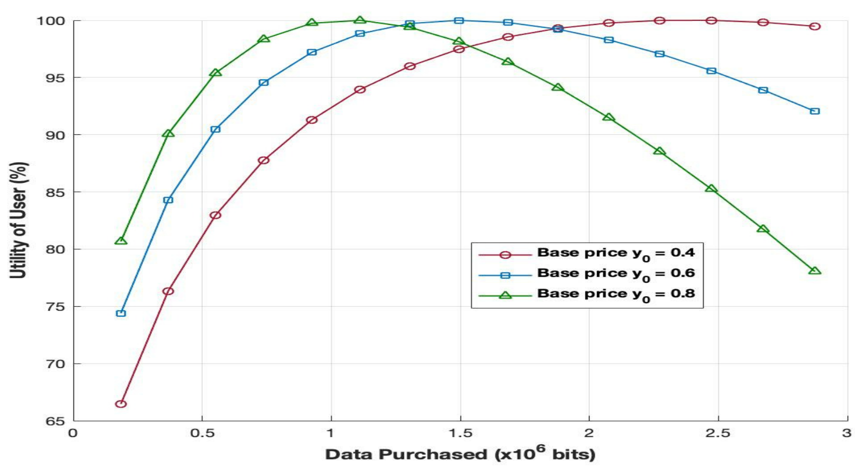

Figure 2.3: User's utility analysis.

In the previous section, it was demonstrated through mathematical proofs that the buyer's utility definition is concave for any price y_0 set by the sellers. Figure 2.3[2] depicts the relationship between the buyer's utility and the quantity of multimedia content purchased, for three different prices set by the seller. The QoE of buyer requesting video content is formulated as a function of their video preferences, as illustrated in Equation (2.2). To examine the impact of video preferences on the user's QoE, the value of γ is adjusted while holding the base price constant at 0.4, and plot the results in Figure 2.4[2]. It can be observed that at lower data rates, the value of γ has a substantial effect on the user's QoE.

The normalized utility of the sellers' alliance is shown in Figure 2.5 [2] for base prices of 0.6,

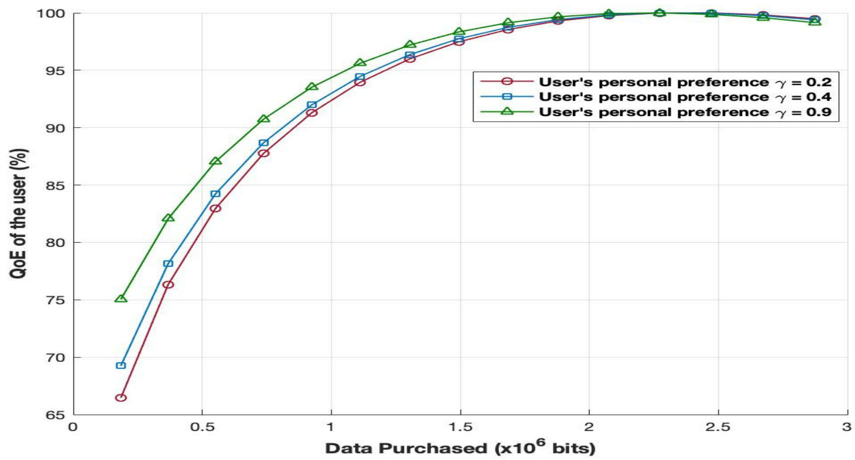

Figure 2.4: Analysis of user QoE for different content preference γ.

0.5, and 0.4, respectively. The graph clearly depicts that the gain is directly related to the quantity of videos transmitted and illustrates how the optimal solution is disrupted if the seller alliance deviate from their mutually agreed selling cost.

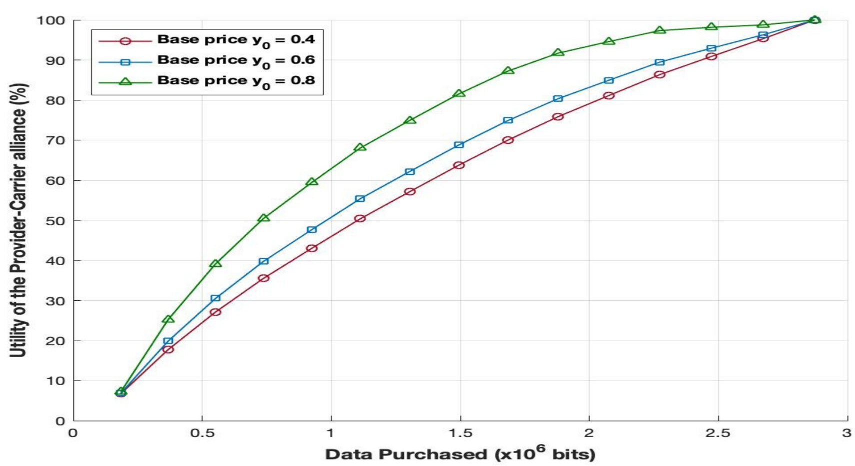

Figure 2.5: Analysis of provider-carrier utility.

The seller alliance utility is illustrated in Figure 2.6 [2] by varying the cost of operation represented by β and α, respectively. The graph shows that as β and α increase, the utility decreases linearly for any cost y_0. Thus, it can be concluded that the initial values of the constant parameters do not impact the proposed utility equations.

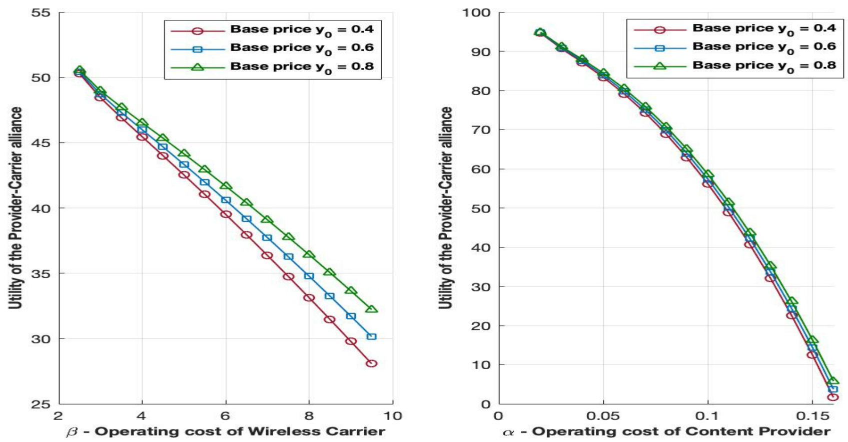

Figure 2.6: Analysis of provider-carrier utility for varying operation cost.

The pricing model proposed in this study prices video frames differently based on their frame length and PSNR, which reflects their importance to the user's QoE. To assess the effectiveness of this scheme, it was compared with a existing pricing scheme based on throughput, where each frame is assigned the same PSNR and bit length, resulting in a fixed cost for the resource.

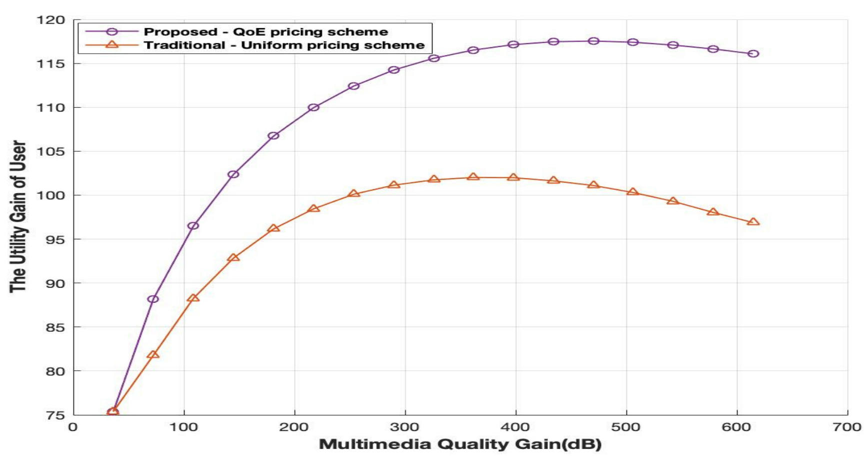

Figure 2.7: Comparison of SMP against traditional uniform pricing.

Figure 2.7 [2] presents the maximum utility achieved by the buyers for both schemes. The results clearly show that the SMP model is significantly better than the existing pricing models. This is due to the Stackelberg game-theoretic solution being used in the scheme to strategically prices frames, with regular packets priced lower and crucial packets assigned higher prices, to improve the QoE of the user.

2.6 Concluding remarks

This chapter introduces a new economic pricing model for video that is sensitive to QoE and is formulated using Stackelberg game theory. The model is designed to work with modern multimedia encoding technique, such as HEVC H.265, which creates media packets with varying levels of quality contribution. Instead of pricing video frames based on their data size, the proposed model prices them based on their quality. The interplay between the seller and the buyer are formulated and solved using a two-stage Stackelberg game-theoretic model. The Nash Equilibrium of the proposed scheme is determined using an iterative algorithm built leveraging the backward induction technique. The numerical analysis conducted show that the developed QoE-sensitive video economic pricing yields higher utilities than traditional pricing models.

This chapter showcase the findings from our preliminary work. Building up on the potential of dynamic pricing, the framework has been extended to NOn-Orthogonal Multiple Access networks in the subsequent chapters.

Chapter 3

NOMA Pricing: Game-Theoretic Resource allotment for NOMA Wireless Networks

3.1 Background

The sixth generation of mobile communication is subjected to network clogging and delay. A promising solution for this is NOMA meaning Non-Orthogonal Multiple Access. However there are still open challenges that are yet to be addressed. This includes standardizing network income and improving the customer satisfaction. To resolve the gap between service price and end user (EU) satisfaction in NOMA enabled networks; this chapter proposes a new approach called Non-Orthogonal Multiple Access Pricing (NOMAP). The hypothesis of

The materials presented in Chapter 3 have been presented at the 2021 IEEE International Symposium on Local and Metropolitan Area Networks (LANMAN) [3] and the 2022 IEEE Wireless Communications and Networking Conference (WCNC) [4] this research is that strategic pricing of data based on quality and permitting EU devices to manage their resources can generate higher utility. Furthermore, the study shows an example of implementation by developing an algorithm that achieves stability in terms of Nash equilibrium. Simulations were run to illustrate the potency of the developed NOMAP framework. The simulation results show that the suggested pricing approach yields better results than the traditional pricing schemes.

3.2 Introduction

NOMA has recently become a common topic of inquiry among researchers owing to its potential as an application for 6G mobile networking and beyond [29]. NOMA is known to offer several advantages including better spectrum effectiveness, superior connectivity, and lesser delay with enhanced reliability [30]. In NOMA works multiple EU devices are able to use the available resource simultaneously in across space, frequency, and time. Yet, problems such as allotment of power to mobile EU, allocation of resources, and NOMA aware pricing. This chapter discusses these issues in detail.

NOMA can be applied in different domains, like code, frequency or time domain [10]. A strategy called Superposition Coding (SC) is used to enable simultaneous multiple access and permit more devices to access the resources simultaneously. Then Successive Interference Cancellation (SIC) is used to recover each communication session at the receiver end. However there is an unresolved problem in power-domain NOMA which is to allocate power strategically to achieve perfect signal recovery, at the same time maximizing network revenue [31] To resolve this issue, this chapter introduces the NOMA Pricing (NOMAP) framework. This framework permits the base station (BS) to adjust the price of the power resource. This way the BS is able to provide satisfactory service without compromising the network revenue.

A critical factor in wireless network is the satisfaction or Quality of Experience (QoE) of the EU devices. Earlier the QoE was evaluated objectively using metrics such as throughput and latency. However in recent times, there has been a switch to subjective measurements such as Peak Signal to Noise Ratio (PSNR) [32]. Though NOMA has exhibited significant enhancements in system performance measured by delay and throughput, their impact on the EU devices' QoE is not clearly understood. This chapter is focused on strengthening the QoE of NOMA by incorporating the amount spent as a component in measurement of satisfaction achieved by the EU.

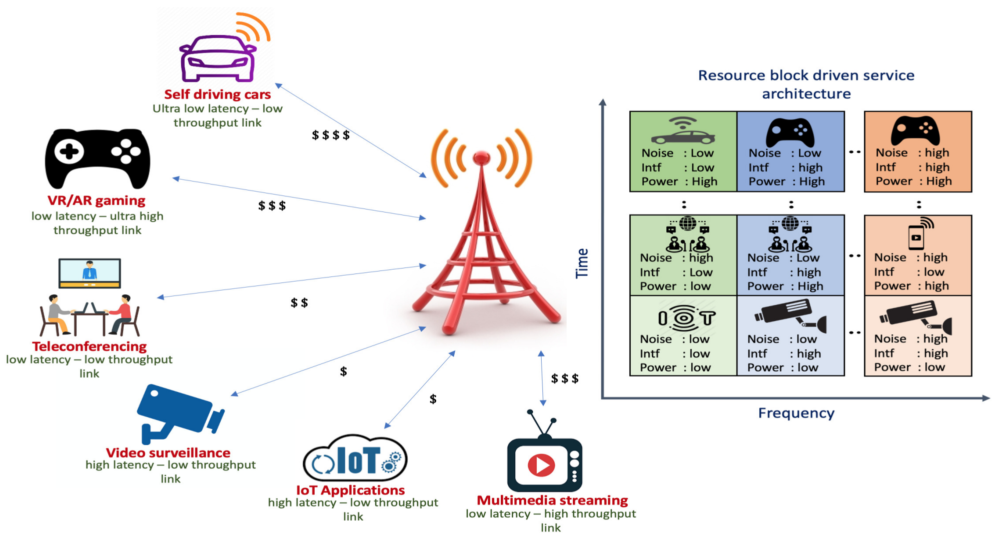

Figure 3.1: QoE aware resource block management and power allotment

The NOMAP paradigm is rooted in the principle of utilizing price as a resource for resource management and power allotment in NOMA to achieve optimal QoE for end-EU devices. The approach allows end-EU devices to have control over the amount of power they want to purchase for NOMA interactions in the down link. Resource blocks, which are allocated across time and frequency, can be subdivided into blocks to serve multiple EU devices simultaneously within a single resource block, as shown in Figure 3.1 [3]. However, assigning resource blocks to EU devices poses challenges due to their dynamic nature. In existing pricing scheme, EU devices may choose a specific block over others, leading to network overloading and profit loss for the BS. To address this issue, the proposed NOMAP architecture leverages pricing mechanisms that take into account noise, interference, and available power to allocate resource blocks. This enables a new device to join a block determined by their QoE demands and application. The primary goal of this study is to demonstrate that regardless of the resource block chosen, both the EU and the BS can achieve high utilities while meeting all QoE demands of the EU.

In accordance with the NOMAP architecture, the BS adopts a pricing mechanism that dynamically alters the prices of the available power resources in each resource block. This approach provides the EU with the freedom to choose the amount of power they wish to purchase, taking into account their unique QoE requirements. Moreover, the EU can select the resource block that offers the most optimal utility for their specific application needs. To maximize the utility for both the EU and the BS, a Stackelberg game-theoretic model was formulated, and the backward induction technique was employed to determine the optimal solution. This process ensures that all available resource blocks are maintained in equilibrium in a stable manner, preventing any negative impact on the network revenue due to the EU's selection of a particular resource block.

The field of NOMA is still relatively new, and there is ongoing scrutiny of its potential applications [33, 34]. Researchers have recently delved into exploring the use of NOMA in various areas, including multiple-input multiple-output (MIMO) systems and NOMA with cognitive radio [35]. Additionally, the prospects of using NOMA in machine-to-machine (M2M) communications are being investigated, along with its integration with other technologies, such as blockchain, to facilitate secure and efficient communication. With the constant advancements in 6G technology, it is highly likely that NOMA will continue to be an essential and dynamic area of research and development for the foreseeable future.

Several researchers have investigated varying aspects of NOMA systems such as virtual resource allotment [36], caching strategies, and effective capacity in the context of delayed quality of service [37]. Furthermore, researchers have investigated the potential applications of NOMA for low-delay Vehicle-to-Vehicle communications and have examined its implications for broadcast and reformed performance [38].

On the other hand, numerous researchers have spent time on addressing key issues in power-domain NOMA to enhance the QoE. For instance, a study [39] investigated the energy efficiency concerns related to NOMA's down link performance in a diverse radio access network over cloud. Another study [40] explored a hybrid analog-digital pre-coding scheme for the BS to maximize the QoE of customer devices. Moreover the work in [40] suggested an energy-efficient algorithm for power allotment in NOMA network. Before introducing NOMA as a suitable network access scheme for 6G and beyond, developing a QoE-pricing strategy that benefits end-EU devices and BSs is crucial. To address this issue, a new framework, named NOMAP, has been established in this chapter.

3.3 NOMA Pricing (NOMAP) model

In this section, NOMAP system model is introduced and its utility equations are presented. NOMAP allows for the maximization of EU satisfaction in the face of varying quality-of-experience (QoE) demands. Apps such as self-driving vehicles, mixed reality games, virtual meeting tools, closed circuit television surveillance, and video streaming account for a significant portion of internet traffic, and it is not fair to treat them all the same. Traditionally, pricing has been based on bandwidth or data usage, without regard for overall QoS. Additionally, the network treats critical and non-critical traffic equally. In contrast, NOMAP's pricing scheme looks at constrains such as the total EU devices, channel interference, and communication link distance, resulting in different costs for different resource blocks. With developed scheme to determine price and transmission power, higher utilities may be achieved.

Popular industries like passenger airways and ride-sharing like Uber are already using QoE-driven pricing schemes. For example, Uber supplies four different ride options with varying prices determined by the QoE requirements. This system enables the optimization of utility for both the mobile EU and the BS while giving different service options to the EU.

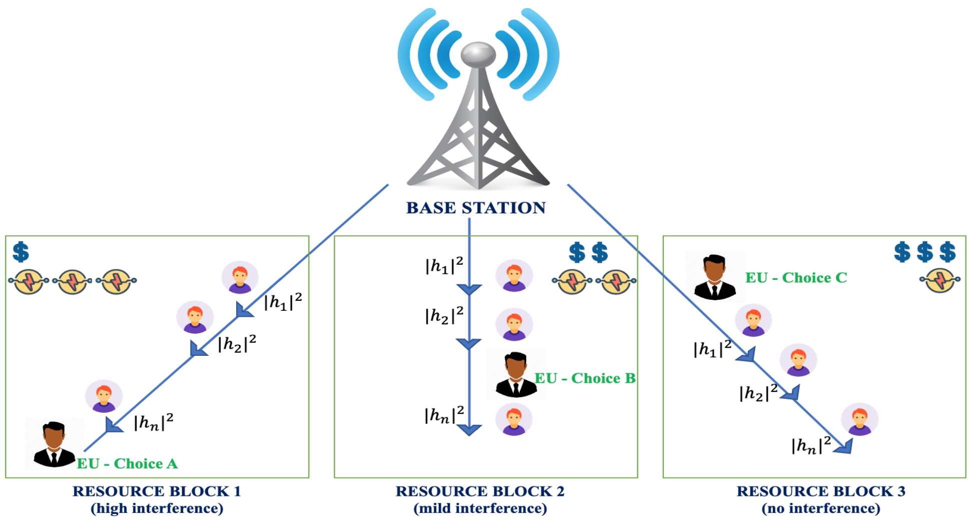

Figure 3.2: NOMA Pricing system model.

The presented system model comprises of a single BS and three NOMA-enabled resource blocks, each with an equal number of active EU devices (n) for simplicity, as depicted in Figure 3.2 [3]. However, the channel gains of the EU devices in each block differ significantly, resulting in varying levels of interference. The first block is characterized by "high interference" due to the proximity of its existing EU devices to the BS, which causes interference and requires the purchase of a substantial amount of power to meet their QoE demands. Therefore, the BS would charge a lower price for power to attract new end-EUs to this block. The third block, in contrast, experiences "low interference" since the existing EU devices are situated far from the new end-EU. This allows for decoding and subtraction of the signals corresponding to the farther EU devices using SIC by the new EU, who can then purchase less power to meet their QoE requirements. NOMAP leverages allots higher price to power resources in low interference setting. The second block exhibits "mild interference" as it has existing EU devices located on either side of the new EU. NOMAP utilizes price as a resource, enabling the end-EU to obtain the best value for their spending across all three resource blocks.

The developed NOMAP system model and utility maximization problem can be extrapolated to larger networks having more resource blocks and varying EU distributions. The objective of the developed methodology is to optimize the QoE for the new EU by pricing resources non-uniformly depending on overall channel gain. By continuously updating the solution when new EU devices join or leave the network, the devices can adopt the NOMAP framework to improve their personal utility gain. Here, the NOMAP framework profits both the EU and the BS by delivering better QoE and resource utilization.

3.3.1 QoE modelling

In the context of a NOMA system, EU selects one of the available resource blocks provided by the BS and subsequently makes a service request to the BS. Typically, there are M resource blocks to choose from, and each block serves n EU devices via the BS. The wireless links between the EU and the BS undergo independent and identically distributed (i.i.d.) block Rayleigh fading and Additive White Gaussian Noise (AWGN). All EU devices in a block share the same physical channel resources, including the frequency spectrum bandwidth, time slots, and spreading codes. By utilizing SIC and SC techniques at the receiver and transmitter, respectively, the transmission rate that a given EU can achieve in resource block R_i can be determined using the Shannon-Hartley theorem.

$$R_i = B \log_2 \left(1 + \frac{P_i \left| h_i \right|^2}{\sum_{k=i+1}^{N} P_k \left| h_k \right|^2 + \sigma^2} \right) \tag{3.1}$$

Here, B represents the allotted bandwidth for transmission, P_i represents the transmitted power, and h_i represents the channel Rayleigh fading between the EU and BS. EU devices that have higher channel gain than the EU are denoted by k and their signals would introduce interference to the EU. The noise of the communication channel is represented by σ^2.

The QoE is measures the satisfaction of the EU in terms of utility maximization for each session. The log model is commonly used to model the QoE equation in wireless communications, as it can make the utility definition concave by subtracting a cost function that is linear. This function is effective in QoE modeling [2, 25]. Hence, the NOMAP QoE can be expressed as a log function of the allotted resources, represented as Equation (3.2):

$$QoE_i = \alpha \log_2 \left(1 + B \log_2 \left(1 + \frac{P_i \left| h_i \right|^2}{\sum_{k=i+1}^{N} P_k \left| h_k \right|^2 + \sigma^2} \right) \right) \tag{3.2}$$

Here, α represents currency gain for the log QoE.

3.3.2 Utility definition of the EU

The price incurred by the EU for utilizing the NOMA resource block is represented as a linear function of the power, denoted by P_i, where cost for EU (i) is denoted by y_i.

$$\psi_{EU} = y_i P_i \tag{3.3}$$

The total benefit of selecting a resource block by the EU can be calculated as the QoE minus money spent, as per the mathematical Equation (3.4). The minimum and maximum power requirements for successful transmission are represented by $P_{i_{\min}}$ and $P_{i_{\max}}$, respectively, where the max power the BS can allot to one of the EUs.

$$U_{EU} = QoE_i - y_i P_i \tag{3.4}$$

$$s.t. \quad U_{EU} \geq 0$$

$$P_{i\min} < P_i < P_{i\max}$$

The EU's optimization issue is to predict the optimal amount of power to purchase for the available NOMA blocks in order to maximize their utility. After solving this optimization problem, the EU can freely pick any resource block that satisfies their budget and QoE requirements.

3.3.3 Utility definition of BS

The BS has two goals: to maximize revenue and maintain a certain level of QoE. To calculate the revenue, the parameter ψ_{TX} is used, which is the cost per unit energy needed to transmit a packet. The value of ψ_{TX} is determined by the frame length (in bits) being transmitted (l), the power allotted for transmission (P_i), the constellation size of the modulation scheme (b), and the bandwidth (B). The value of λ represents the payoff value per unit energy consumed.

$$\psi_{TX} = \lambda \frac{l.P_i}{b.B} \tag{3.5}$$

The BS's utility for serving the EU in one of the NOMA resource blocks is determined by the revenue earned from the EU subtracted by the cost of transmitting data.

$$U_{BS} = y_i P_i - \lambda \frac{l.P_i}{b.B} \tag{3.6}$$

$$s.t. \quad U_{BS} \geq 0$$

The BS does have some control over the resource blocks, as it can compute the cost y_i for each block. The BS's goal is to set the cost for each block in such a way that it maximizes its overall utility, regardless of which block the EU chooses. This can be prepared as an optimization problem, where the BS seeks to maximize its expected revenue minus the expected transmission cost, subject to constraints on the allotted power to EU and the total power with at the BS.

3.4 Game-theoretic solution

In this particular situation, both the EU and BS are rational entities, seeking to enhance their profits. To simulate their interactions, a Stackelberg game-theoretic model is employed, where the BS plays the role of the leader and determines the cost initially, while the EU plays the role of the follower and chooses the power resource to purchase. The optimal strategies for both parties, represented as $\{P_i^*, y_i^*\}$, are obtained using backward induction to calculate the Nash Equilibrium solution. Nash Equilibrium refers to the state where neither party has a merit to deviate from their selected strategy [41].

Using the NOMAP architecture, the game is played independently for each of the available M resource blocks, and a Nash Equilibrium solution is obtained for each block. By doing so, the system ensures the existence of a stable solution for every single resource block. Subsequently, the EU can assess each of the solutions and select the one that maximizes their utility while still satisfying their QoE requirement.

3.4.1 Strategy to maximize EU utility

The analysis starts by focusing on the EU and employing the technique of backward induction. As the EU is not privy to the BS's strategy, a response equation that links the variables, P_i and y_i, is developed. The response equation ensures that the EU always selects the option that provides the maximum utility.

Property 1: *The utility function of the EU is concave with respect to its transmission power P_i purchased [3].*

Validation: The utility equation can be transformed into a concave function by subtracting a linear cost function from the two-level log QoE model, as explained in previous studies [3].

Property 2: *A unique Nash equilibrium solution for the EU's power selection problem exists in the NOMAP architecture [3].*

Validation: Because the utility definition is concave, we can obtain a unique relationship between the cost y_i determined by the BS and the power P_i that the EU purchases by setting the derivative of the equation to zero.

As the Nash Equilibrium solution is valid across all NOMA blocks, the solution can be computed once and utilize it for each resource block by substituting relevant values. This helps in saving computational resources and reducing complexity.

3.4.2 Strategy to maximize BS utility

The person who is leading the game has knowledge about the strategy developed by the EU. This strategy has a fixed relationship. By incorporating this relationship into the leaders' utility definition, the variables that are not known can be decreased from two to one. Using the two lemmas (lemma 1 and lemma 2) outlined in chapter 2, the Nash Equilibrium y_i^* can be calculated using the Newton method. The details of the procedure is outlined in Chapter 2.

Validation of Lemma 1: The utility equation of BS can be transformed into a function of price y_i by minimizing the two unknown variables to one. It can be observed that the function is both real and can be differentiated.

Validation if Lemma 2: Because the Nash equilibrium transmission power is limited to a specific range of values, namely $P_{i\min} < P_i < P_{i\max}$, the cost established by the BS is also constrained within a range of $y_{i\min} < y_i < y_{i\max}$. To determine the optimal cost y_i^*, a search needs to be conducted within these intervals.

Once the computation is completed, the BS will communicate the price y_i^* to the EU. Using the previously derived relationship, the EU can then calculate the power P_i.

Algorithm 2 NOMA Pricing framework using Stackelberg game-theoretic model

1. **Initialization:**
   - 1.1. set the cost variables α and λ.
   - 1.2. set the channel parameters: bandwidth B, interference H and noise σ.
   - 1.3. Set the transmission parameters: length of packet l and modulation constellation size b.
   - 1.4. set the simulation iteration count X.
2. **Iterations:**
   - 2.1. The algorithms determine the optimal responses P_i^*, y_i^* for all M resource block configurations, resulting in M distinct Nash Equilibrium solutions.
   - 2.2. **For** i=1: M (iterate through resource blocks)
   - 2.3. Initialize $U_{BS}^m = U_{EU}^m = P_i = y_i = 0$
   - 2.4. Let $\chi = y_{i\min} : X : y_{i\max}$
   - 2.5. **For** j=1: Y (iterate through price range)
   - 2.6. Set $\gamma = \chi$(i)
   - 2.7. Compute $u_{BS}(\chi(j))$
     - 2.7.1 if $u_{BS}(\chi(j)) \geq U_{BS}^m$
       - 2.7.1.1 Update $U_{BS}^m = u_{BS}(\chi(j))$
       - 2.7.1.2 Set $y_i = \gamma$
       - 2.7.1.3 Calculate P_i using EU's derived strategy
     - 2.7.2 End **if**
   - 2.8. Determine the values of U_{BS}^m and U_{EU}^m using the utility definitions.
   - 2.9. End **for**
   - 2.10. Choose the max U_{EU}^m as $U_{EU}^{m^*}$. Alternatively, a different constraint can be leveraged to choose the resource block.
   - 2.11. Recompute the corresponding values of $\{P_i^*, y_i^*\}$ and also obtain the $U_{BS}^{m^*}$.
3. **Output:** The algorithm determines the Stackelberg game-theoretic equilibrium $\{P_i^*, y_i^*\}$ for all the resource blocks. A resource block is then picked based on overall utility and QoE requirement. The corresponding utilities of BS and EU are computed.

The analysis presented above serves as a foundation for an algorithm that can be used to implement the NOMAP framework and calculate the Nash Equilibrium. The algorithm 2 [3] presented above, selects the resource block that yields the highest utility. However, depending on the specific application, the algorithm can be customized to select the resource block in a different manner.

3.5 Numerical study

To evaluate the effectiveness of the developed model and compare its performance against economic pricing used in OMA, MATLAB simulations were conducted. The initial values were set at $\alpha = 5$ and $\lambda = 2$, and the channel SNR was set to $25dB$. A modulation size of 2 and a packet length of 10000 were chosen for the simulations. The iteration length was set to $X = 500$ to obtain more accurate results.

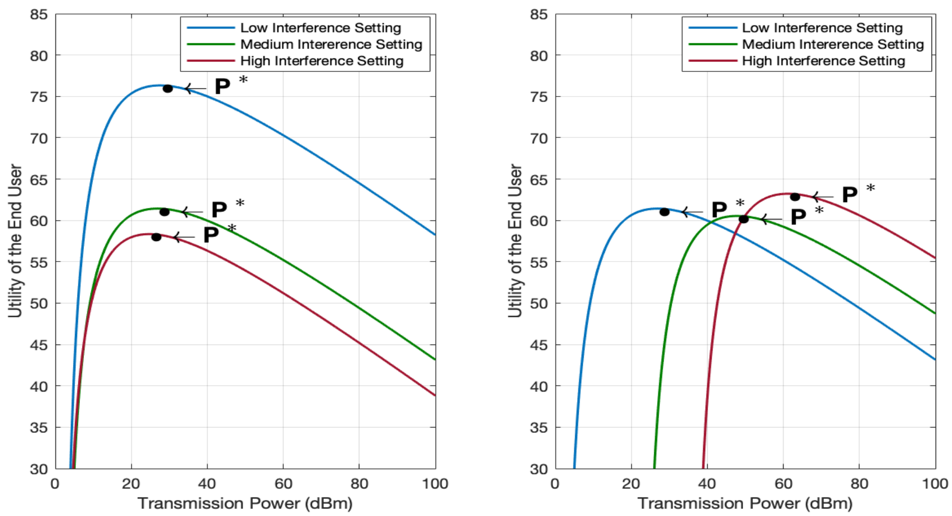

Figure 3.3: EU's utility comparison

Previous section demonstrated mathematically that the log QoE model ensures the EU's utility is always concave. Existing scheme treats all resource blocks (interference levels) as equal, resulting in the Nash Equilibrium price leading to varied utilities for the EU, depending on their chosen resource block, as depicted in Figure 3.3 (left). However, NOMAP utilizes non-uniform pricing to enable the EU to achieve comparable utilities, regardless of the interference levels they choose, as illustrated in Figure 3.3 (right)[3].

Wireless channel quality is subject to fluctuations over time, and as noise levels rise, the bit

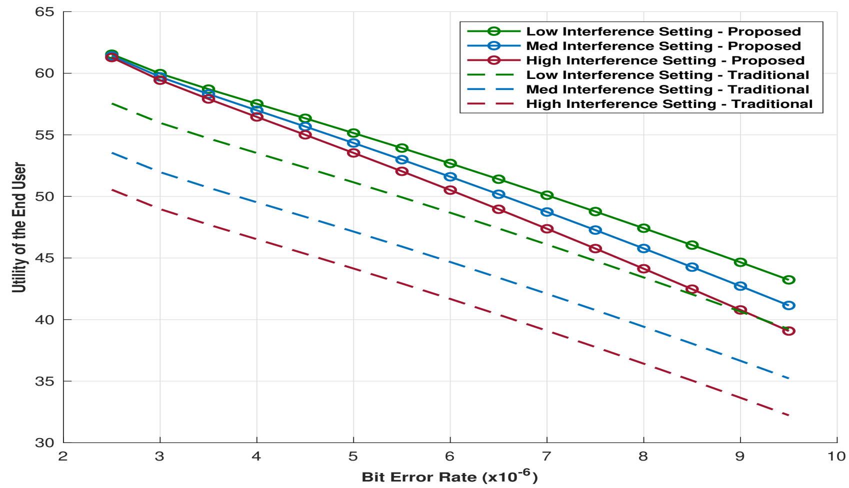

Figure 3.4: Effect of channel conditions on EU's utility

error rate (BER) also increases. Figure 3.4 [3] compares the effect of BER on the EU's utility. The BER has a noticeable effect on the overall utility of the EU. However, in traditional pricing systems, the impact of a declining channel is directly proportional to the interference levels. In contrast with NOMAP's pricing approach, where price is treated as a resource, the effect of a deteriorating channel is similar across all resource blocks, resulting in comparable impacts on the EU's utility, regardless of their selected resource block.

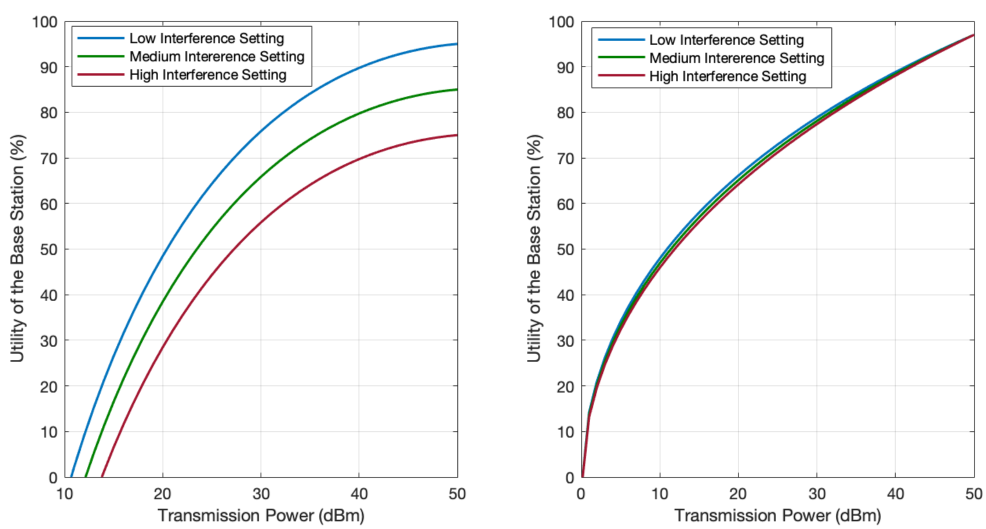

Figure 3.5: BS's utility comparison

The framework of resource block-based wireless communication poses two new challenges for the BS. Firstly, it may face situations where all EU devices select a single resource block, resulting in an imbalanced network. Secondly, the revenue generated from resource blocks is non-uniform. Figure 3.5 (left) depicts the traditional pricing approach, where the maximum achievable utility varies across the resource blocks. In contrast, the NOMAP framework benefits both the EU and the BS. By treating price as a resource, the EU pays a higher price for a low interference channel and a lower price for a high interference channel. Non-uniform pricing guarantees that the BS achieves high utility across all its resource blocks, as demonstrated in Figure 3.5 (right) [3].

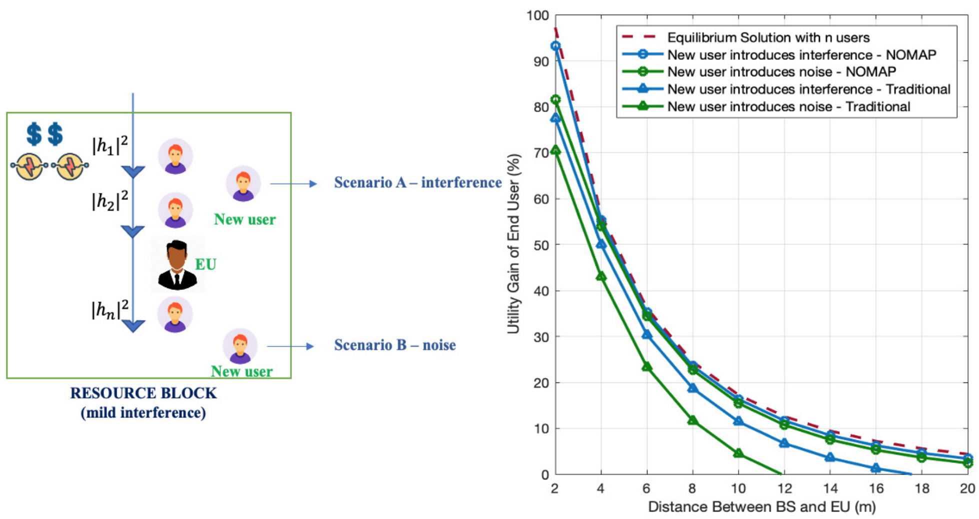

Figure 3.6: Impact of a new EU on NOMA resource blocks

In time-varying mobile networks, EU devices can join or exit a NOMA block at any instant. Every instance of a new EU entering a block with an existing EU, the utility of the latter may be impacted. If the new EU is closer to the BS than the existing EU, their signal may cause interference (scenario A) to the network. On the other hand, if the new EU is farther away, their signal may cause noise (scenario B) to the existing EU. Figure 3.6 [3] investigates this situation by comparing existing price with NOMAP. With NOMAP, the reduction in utility for the existing EU is minimal under scenario A and insignificant under scenario B. In contrast, we observed a considerable reduction in utility for the existing pricing techniques as a new EU cause interference.

The numerical analysis was also conducted on video data obtained using MPEG-4 H.265 codec. Three multimedia clips were encoded using four different GOP configurations IIIIII..., IPIPIPIP..., IBPIBPIBP..., and IBBPBBPBBP....

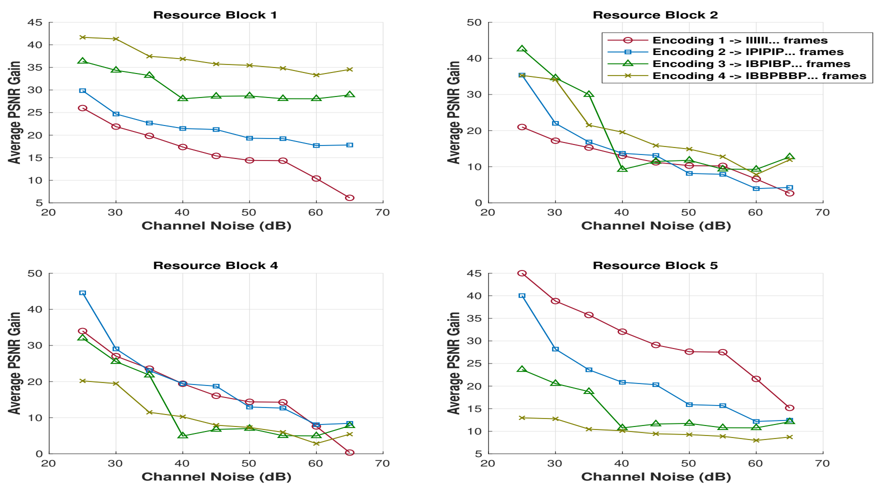

Figure 3.7: Evaluation of NOMAP using multimedia data

The PSNR improvements achieved by EU devices are compared to the channel conditions of the four different resource blocks in Figure 3.7 [1]. When there is no interference (Block 1), the price of the resource block is high, so re-transmit rates are low and EU devices tend to buy more P and B frames. The IBBPBBPBBP... encoding scheme yields the highest utility because price is considered a resource. In a high interference scenario (Block 4), the price of using the resource block is low, so EU devices would prefer to buy only I frames. Since the re-transmit rate is high, it would be beneficial for the EU devices to purchase independent I frames instead of B and P frames, which rely on successful transmission of ancestor frames. Fig. 5 shows how EU preferences for different encoding schemes among the resource blocks are transmitted. These results confirm the effectiveness of the NOMAP framework for 6G and beyond.

3.6 Concluding remarks

In this chapter, the NOMAP framework was introduced, which involves pricing the selection of NOMA resource blocks alongside power allotment. The framework was analyzed in a simplified NOMA network scenario with one BS and three NOMA resource blocks, and the Nash Equilibrium solution was obtained under NOMAP. The analysis indicated that NOMAP results in high utilities for both the BS and EU. An algorithm for implementing this framework was also developed. Simulation results demonstrated the potential of NOMAP to enhance total number of EU devices supported, increase BS earnings, and simultaneously boost the EU's QoE.

Chapter 4

Human Cognition Aware Pricing: Prospect-Theoretic Augmentation to NOMA Pricing

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4.1 Background

The evaluation of modern communication systems Quality of Experience (QoE) heavily relies on human cognition. The Expected Utility Theorem (EUT) is a commonly used mathematical model to describe humans' decision-making processes. However, recent research has shown that EUT is not always applicable, as users' decision-making abilities can deviate from EUT under certain circumstances. To address this issue, an auxiliary theory known as Prospect Theory (PT) [42] has been proposed.

The materials presented in Chapter 4 have been presented at the 2022 IEEE Intermountain Engineering, Technology and Computing (IETC) [5], 2020 IEEE Intermountain Engineering, Technology and Computing (IETC) [6] and submitted to IEEE Internet of Things Journal (under 2nd round of review) [1]

Meanwhile, Non-Orthogonal Multiple Access (NOMA) has been advocated as a fitting protocol to increase network capacity performance. However, the impact of NOMA on user QoE is not fully explored. In a previous chapter, NOMA pricing (NOMAP) model was designed to optimize end-user QoE and base station (BS) profits. NOMAP also provided solution to power selection and resource allocation issues.

This chapter proposes integrating theoretical models from the PT into the NOMAP model to enhance the attainable user QoE. The PT QoE model for NOMA communication is derived using the weighting function and value function. Simulation results of a NOMA network demonstrate the potentials of the PT QoE modeling in wireless multimedia communications.

4.2 Introduction

NOMA, a relatively new method of accessing networks, has garnered attention as a promising solution to deal exponential increase in number of internet-ready user equipment and improving communication efficiency, according to a report by Cisco [17]. In power-domain NOMA, the spectrum with the provider is divided into multiple blocks with varying properties like latency and throughput. Users are then grouped together in each block and their data is combined and encoded at different power levels to transmit a combined signal. This technique allows base stations to provide faster service to more users, leading to improved spectral efficiency.

However, there are several issues with NOMA-based wireless communication, including how to distribute power among users, pricing resources, and allocating resources fairly [3, 4]. In the previous chapter, a new pricing framework called NOMAP was introduced to address some of these issues. With NOMAP, users can choose which resource blocks to use for data transmission, and base stations can dynamically set prices based on factors like interference and network demand. Users can also adjust their encoding power to meet their QoE demands while still saving money. The NOMAP was built using the properties of Expected Utility Theorem (EUT). However, EUT assumes users are rational and unaffected by outside factors, which is not always true. To address this issue, Prospect Theory (PT) was proposed [16].

PT takes into account human attributes such as risk-aversion and risk-seeking in modelling user perception, thus resolving the issue mentioned above. PT has been increasingly used in wireless communication and multimedia networks research. For example, it has been used to model rational behavior in UAVs [43] and to capture subjective users' perceptions in autonomous networks [44, 45]. PT based pricing techniques have been proposed for several apps blockchain systems, where deep reinforcement learning and PT are used to balance risks and rewards [46]. Furthermore, dynamic value and weighting functions have been proposed to efficiently capture human behavior [47].

In this chapter, PT has been incorporated into the NOMAP framework to further investigate end-user QoE. The PT QoE model for NOMA is formulated with the help of the weighting and value equations is been proposed. Furthermore, a NOMA network is simulated to measure PT NOMA pricing model efficacy. The simulation results reveal the potentials of using PT in modelling QoE equations.

4.3 Prospect-Theoretic augmentation to NOMAP model

In this chapter, an investigation is carried out on a network that implements NOMA, which comprises 'm' blocks and 'n' devices in every block. The user devices in each block receive their signals concurrently using NOMA, which are overlapped at different power levels. These users then use the successive interference canceller to extract the data from superimposed signal. The user with highest channel gain has their information at the top of the carrier signal, resulting in no interference from other user data. However, as the number of users and their distance from the base station increases, the data becomes more vulnerable to interference, necessitating more power for encoding such signals.

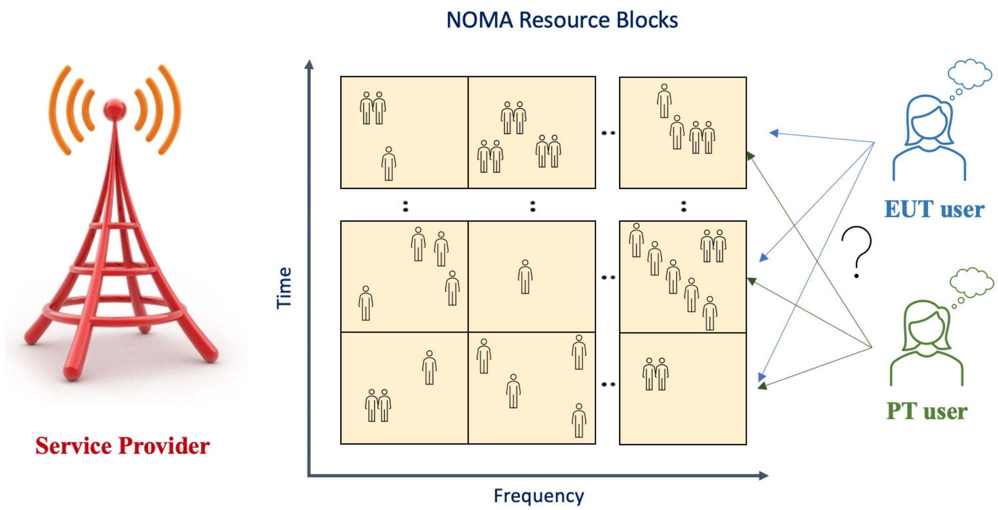

Figure 4.1: PT Augmentation to NOMAP Model

The considered network in this research is the NOMAP network displayed in Figure 4.1 [5]. The NOMAP framework enables users to freely select their blocks and power options. The figure portrays a EUT and a PT user, who possess the same QoE demand and request identical data. In the previous chapter, which employed the EUT QoE model [3], it was discovered that the user's resource block selection was insignificant because the price varied in each block. Consequently, the EUT user could always attain their QoE objectives by adjusting the power quantity purchased in any of the resource blocks. However, in this chapter, the central inquiry is whether PT user favors a block to save money or enhance QoE.

The EUT presumes that all users are rational, objective, and unaffected by real-life experiences. Nonetheless, due to distortions in perception caused by human cognition, a user's perceived QoE may differ significantly from the true QoE (it could be higher or lower). To explain the deviation from the EUT, Kahneman and Tversky developed a probable scenario [42], which is presented in the table below.

In the initial game, if the player chooses option A, they have an 80% chance of winning

Table 4.1: Illustration : Decision-making under risk - EUT vs PT

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

\$4000, while option B guarantees a win of \$3000. Based on EUT, the expected utilities of options A and B are \$3200 (0.80 X 4000) and \$3000 (1 X 3000), respectively. In the subsequent game, option A and B provide the player with a 20% and 25% chance of winning \$4000 and \$3500, respectively. EUT forecasts expected utilities of \$800 and \$875 for options A and B, respectively.

However, when presented to a random group of participants, it was noticed that 80% selected option B in the first game, defying EUT and exposing risk-averse behavior in humans, who prefer a certain win over a likely one. In contrast, in the second game, 65% of the participants picked option A, displaying a risk-seeking attitude towards low-probability events. Therefore, the QoE equation of the user should integrate the PT model to consider these preferences. PT posits that a weighting function, as proposed in proposition 1, uses different weights for low-probability and high-probability options to map the user's subjective perception to the true perception.

Proposition 1: *The properties of a weighting function are as follows: (a) It must have values of 0 and 1 for inputs of 0 and 1, respectively. (b) The function should have a unique inverse, denoted as w^{-1}, which is also strictly increasing, mapping the interval $w(\varepsilon) : [0,1] \xrightarrow{onto} [0,1]$. (c) Both the weighting function w and its inverse w^{-1} should be continuous functions.*

After careful review, Prelec function [48], a strictly non-decreasing function $w(\epsilon) : [0,1] \to [0,1]$, which satisfies *proposition 1* was chosen to model the user QoE equation.

$$w(\epsilon) = \exp\left(-\beta(-\ln \epsilon)^{\alpha}\right), \quad 0 < \epsilon \leq 1 \tag{4.1}$$

The Equation (4.1) uses ϵ, which is the unweighted content preference normalized between [0,1], and $w(\epsilon)$, which is the PT weight for content preference modeled using the Prelec function. The variables α and β are non-negative parameters. The value of α determines whether Prelec function is concave or convex. When $\alpha \geq 1$, the equation is convex for lower weights and concave for higher weights, and the situation is reversed when $\alpha \leq 1$. The point of inflection between the strictly concave and strictly convex regions is controlled by β. Figure 4.2 provides an illustration of how α and β affect the weighting function.

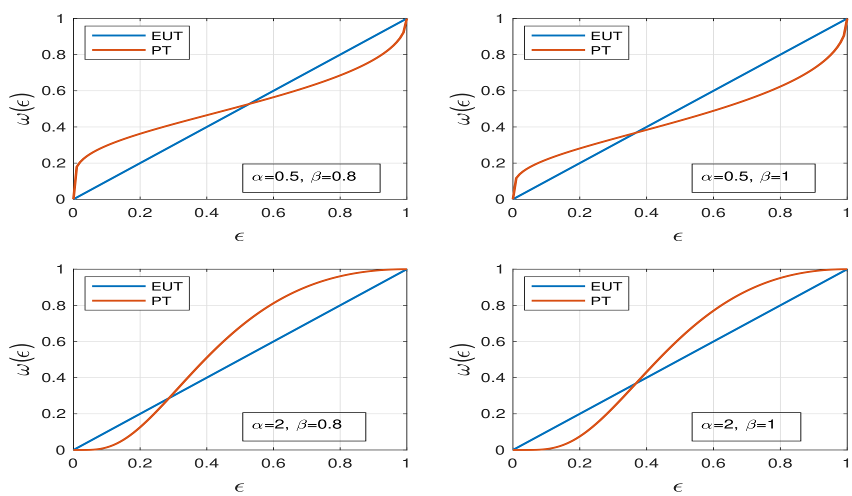

Figure 4.2: Impact of α and β on Prelec weighting function $w(\epsilon)$

The asymmetrical and s-shaped value function proposed by PT is designed to capture the loss averse effect, as losses tend to hurt humans more than gains excite them. The characteristics of this value function is described in *Proposition 2*, and its formula is shown in Equation (4.2) [16].

Proposition 2: *The following are the properties of a value function: (a) it is defined based on digression from a reference point; (b) it is generally concave when considering gains and convex when considering losses; (c) it is steeper when considering gains as compared to losses.*

$$v(x_m) = \begin{cases} x_m^{\kappa}, & \text{for } x_m \geq x_m^* \\ -\lambda(-x_m)^{\kappa}, & \text{for } x_m < x_m^* \end{cases} \tag{4.2}$$

Positive parameters κ and λ control the steepness and shape of the value function. The variables x_m and x_m^* represent the actual achieved gain and projected gain of user devices, respectively. The user's gain, x_m, is a measure of their perceived satisfaction during a session in the NOMA network and can be represented using a log function as shown below.

$$x_m = \gamma \log_2 \left(1 + B \log_2 \left(1 + \frac{P_i \left|h_i\right|^2}{\sum_{k=j+1}^{N} P_k \left|h_k\right|^2 + \sigma^2}\right)\right) - C \tag{4.3}$$

The variable B refers to the bandwidth acquired for data transmission. P_i and h_i represent the transmitted power and gain of the channel between the end user and the base station, respectively. The channel noise power is determined by σ^2. The user experiences interference caused by the sum of P_k and h_k for k users with higher channel gains. γ and C denotes the reward currency for the log QoE and money spent by the user, respectively.

The users' QoE in mobile communications network can be expressed as the result of multiplying the chance of the user device selecting a block by the benefit (QoE gain) received from that block.

$$QoE = w\left(p_m\right) v\left(x_m\right) \tag{4.4}$$

4.4 QoE optimization and PT NOMAP modelling

In NOMA, the interactions among user devices and the base station can be modeled as a game-theoretic problem. To solve this problem, different types of games can be used depending on the utility equations involved. For concave utility equations, a Stackelberg game-theoretic model is utilized. Conversely, non-concavity in utility functions find Best Response game is more appropriate. These games are solved using backward induction techniques that enable the base station to establish the appropriate cost for resources based on the user's strategy. While strategies that enable the seller to maximize revenue are previously investigated, this research aims to simultaneously boost user QoE.

The primary goal of PT user is to optimize the power consumption for a given cost set by the base station for a particular block. In other words, the power must be optimized to ensure efficient data transmission and reception. The optimal power value, represented as P_i, should fall between the maximum and minimum power limits denoted as P_{max} and P_{min}, respectively. The power needed to successfully encode and transmit meaningful information is represented by P_{min}, while the maximum power available with the service provider for one user i in block m is represented using P_{max}. This optimized power is determined for all the possible resource blocks available for data transmission by the user.

The concavity of the gain function x_m is introduced through the log function in utility equation. Using the second-order derivative, it is easy to prove that the equations is concave and the optimal P_i to maximize utility gain can be computed from the first-order derivative. For the initial rounds of transmission the EUT solution determined from Equation (4.3), is leveraged to find the optimized value x_m^*. Once an optimal solution is stable, the PT Equation (4.4) is used to compute QoE.

If a value function that follows the postulates of PT is utilized, the optimal solution to achieve highest QoE should be a monotonically increasing function. Therefore, the optimal solution can be achieved by selecting monotonically increasing values of power for the end-user.

Algorithm 3 Prospect-Theoretic NOMA QoE Optimization

1. **Initialization:**
   1.1. The system parameters α, β, κ, and λ are initialized.
   1.2. The total number of resource blocks, m, is defined, and each resource block is 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 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 are obtained as the output.

The study employs a PT value function with specific properties that require careful consideration when distributing resources. Oversupplying resources may result in a considerable reduction in QoE. To address this issue, a curve smoothing function is utilized to limit abrupt changes in the transmission power assigned to the PT user. An algorithm, termed Algorithm 3 [5], is developed to determine the right power for transmission based on the isolation, risk seeking, and loss-aversion behaviors observed in people. During favorable channel conditions, users tend to be more risk-taking to achieve a higher QoE. However, in the event of a loss, users become more cautious and attempt to minimize any further losses. If the loss is too severe, users may disregard the situation altogether.

4.5 Numerical study

Simulation were carried out in MATLAB to test the effectiveness of their proposed PT-NOMA pricing strategy compared to traditional uniform pricing (EUT-uniform) and traditional pricing based on the expected utility theory (EUT-NOMA). The simulation was performed on a simple NOMA network, and the weighting function coefficients were set to $\alpha = 0.5$ and $\beta = 5$. The value function coefficients were set to $\kappa = 0.5$ and $\lambda = 3$, and SNR was altered between the range $2dB$ and $60dB$, respectively. The cost parameter in the gain equation was set to $\gamma = 10$.

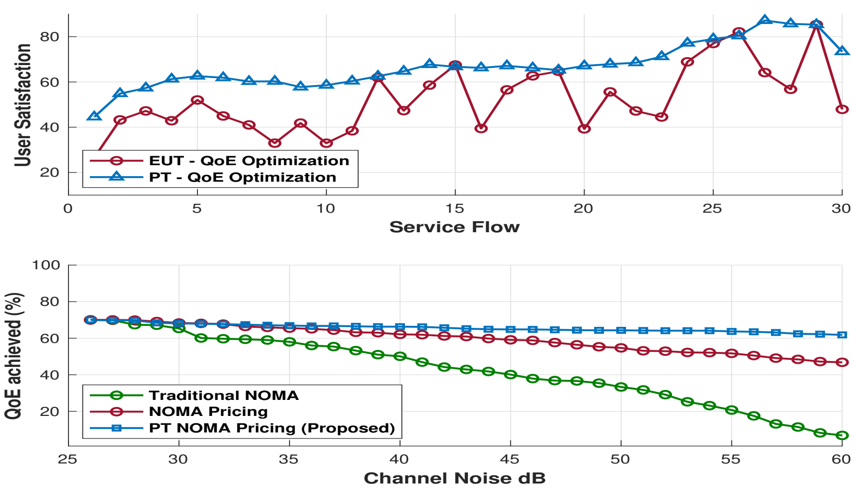

Figure 4.3: QoE and user satisfaction achieved using Prospect Theoretic NOMA Pricing

In Figure 4.3 (top) [5], a comparison is made between the EUT-based NOMAP solution and the proposed PT-optimized NOMAP solution on a noisy channel with AWGN. With rapid fluctuations in the wireless channel, the EUT solution experiences significant fluctuations, resulting in user dissatisfaction as evidenced by the steeper curve at the loss side of the value function in Equation (4.2). However, the proposed PT optimization overcomes this issue by strategically smoothing out the transmission power, thus reducing the fluctuations. Additionally, it is important to highlight that QoE is a monotonically increasing function that is preferable for achieving the best utility.

In Figure 4.3 (bottom) [5], a comparison of the achieved QoE against the channel noise is presented. In the conventional approach, as noise increases, the QoE decreases. However, with NOMAP, users can purchase more power at a lower cost as the channel conditions worsen, resulting in better QoE. In contrast, the PT approach is designed to maintain stable QoE in a time-varying channel using an acquisitive approach. Therefore, by using the suggested PT NOMAP model, the PT users obtain the highest QoE. Nonetheless, it should be observed that EUT user spends lesser money than the PT user. This shows that the PT user is seeking risk to accumulate QoE.

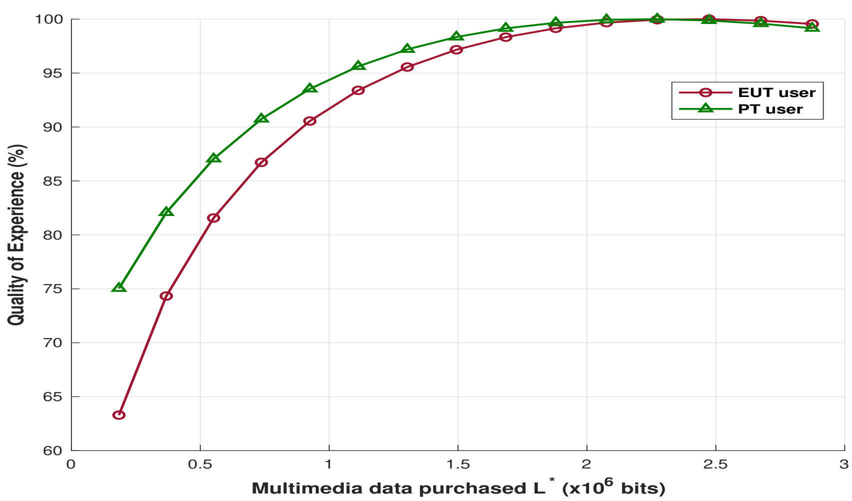

Figure 4.4: QoE analysis with respect to data purchased

In the following simulation, two users were considered who followed the QoE models using EUT as shown in equations (3.2) and PT as shown in Equation (2.4). A channel with realistic characteristics such as error rate of $1e^{-6}$ and signal to interference and noise ratio of 30dB was modeled. The base price for the videos y_0 was fixed at 0.4. The QoE was then simulated for both users. The results shown in Figure 4.4 [6] illustrate that PT user can obtain better QoE gain despite of purchasing lesser power under identical channel conditions from the base station.

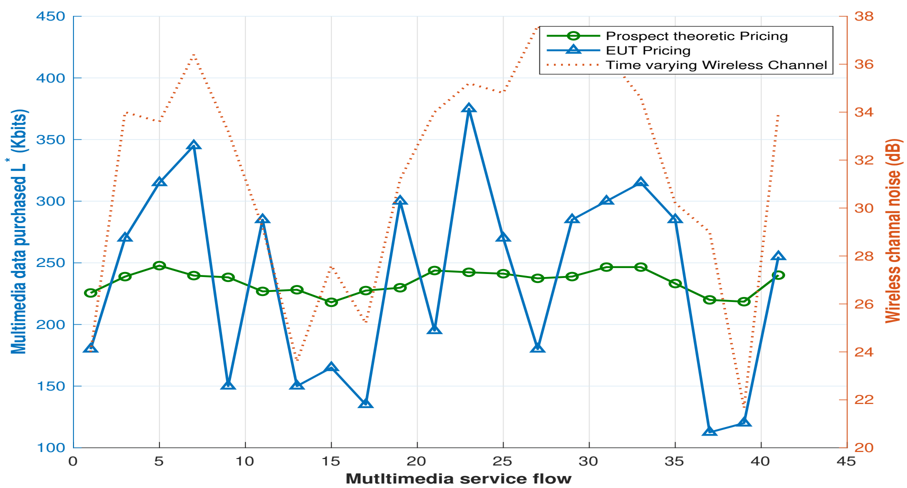

Figure 4.5: Prospect pricing on time varying channel

Superior performance was observed for the PT user in a channel that was recovering, while the EUT user had an apparent advantage while obtaining content over a channel that is noisy and deteriorating. However, in a realistic scenario, the wireless channel experiences continuous time variation, and to assess the efficacy of the solutions, a time-varying wireless channel was considered. As illustrated in Figure 4.5 [6], the EUT user's requested data amount fluctuated significantly, rendering it challenging for user device to accomplish their QoE objective. In contrast, the PT solution ensured that user QoE demands were met despite the variations in channel quality.

The QoE of a user depends on the amount of power they purchase. In Figure 4.6 [5], the optimal power required for both EUT and PT users to achieve the highest utility is shown. The simulation was set-up on a link with high interference and throughput, with and without permitting users to jump among different blocks. The outcome of the experiment indicated that the EUT user, who did not use dynamic block selection, experienced substantial variation as they modified their power purchase to counteract the constantly fluctuating noise. Conversely, the PT user's performance was notably superior since they opted to alternate between blocks in order to sustain a consistent QoE. Additionally, the PT user with dynamic block selection was able to obtain the same level of QoE as the EUT user while purchasing the least amount of power, as inferred from the figure.

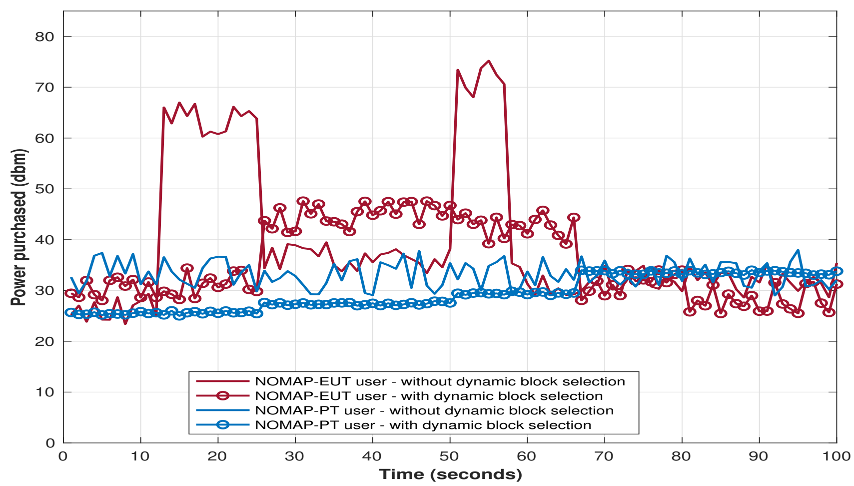

Figure 4.6: Prospect pricing influence on power purchasing behavior of user

It is essential to assess the effect of user QoE with increase and decrease in the number of users in NOMA blocks. This is because the blocks are dynamic and can have new users joining or existing users leaving at any time. To investigate this, simulations were conducted by adding more user devices and thereby introducing interference. Figure 4.7 [5] illustrates that traditional pricing (without NOMAP) significantly affects the QoE of the EUT user as user count in the block increases, due to the uniform pricing scheme where all users pay the same price regardless of the number of users. However, NOMAP mitigates the impact on QoE by decreasing the cost of power as interference increases. Moreover, the PT-based NOMA pricing scheme is even more effective in nullifying the impact on QoE. These findings suggest that power-domain NOMA communications can greatly benefit from the PT-based NOMA pricing scheme in the future.

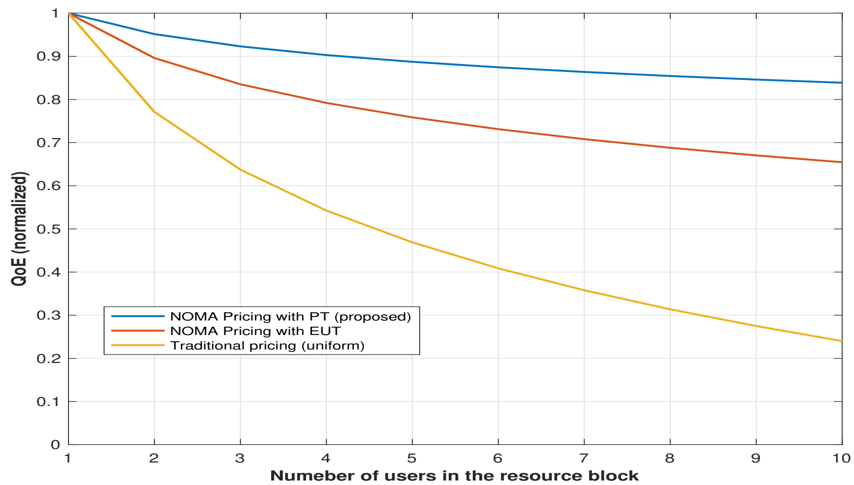

Figure 4.7: Impact of additional user on NOMA resource block

4.6 Concluding remarks

As wireless communication continues to grow and network spectral efficiency decreases, finding effective solutions to satisfy the increasing demand for efficient network access schemes becomes critical. While NOMA technology is a potential solution, it still faces hurdles, such as strategic pricing and dynamic allocation of resources. To address these issues, NOMAP, a novel QoE pricing framework for power-domain NOMA communication, was introduced in the previous chapter. The aim of NOMAP is to simultaneously improve service provider income and user QoE.

In recent times, PT has gained spotlight has it has proved efficient to model people's cognition of services obtained. Therefore, the weighting and value function from PT were leveraged to improve NOMAP framework. The mathematical modelling of utility functions, discussion of optimization solutions, and provision of an implementation reference algorithm were followed by simulations to investigate the NOMAP framework with and without PT rules. The results revealed that the integration of PT principles resulted in a significant decrease in the transmission power needed to satisfy QoE requirements. Additionally, in a dynamic environment, incorporating PT into NOMAP improved user satisfaction considerably. These findings emphasize the need for incorporating fundamentals from PT into QoE modeling to enhance the effectiveness of power-domain NOMA communication.

Chapter 5

Customer driven Pricing: Auction-Theoretic Solutions to Promote Relay Communication in D2D enabled NOMA Network

5.1 Background

Power-efficient communication methods are becoming a necessity as we see a significant increase in videos-driven applications pushing the current wireless networks to their limits. To tackle this, a solution to enhance coverage area, spectrum, and energy efficiency for 6G wireless access networks is developed called Non-Orthogonal Multiple Access (NOMA). To supplement this, Device-to-Device (D2D) relaying was also developed to assist with power

The materials presented in Chapter 5 have been presented at the 2023 IEEE International Conference on Communications (ICC)[7].

efficiency by using shorter distance between the relay and the receiver.

In this chapter, a NOMA power allocation approach in a wireless network that supports D2D relay communications is presented. Here, auctioning techniques for power purchasing to explore relaying devices was examined. The central theme of this chapter is to show that our proposed approach in the NOMA relay framework can significantly enhance users' Quality of Experience (QoE) and maximize benefits for participating relays. In order to do this, two auctioning techniques were developed. This includes first and second sealed price auction, for power allocation. Out of the two techniques, Vickery-Clarke-Groves (VCG) second price auction proved to be a suitable paradigm to increase user QoE and reward participating relays' power transmission based on simulation runs. It was also revealed that NOMA Relay networks are sustainable and can bring down the net power transmitted to meet user demands.

5.2 Introduction

As NOMA serves multiple users simultaneously using the same resources, it is considered to be a hopeful technology for energy-efficient green wireless networks [49]. In NOMA downlink communication, the base station broadcasts contents to all users by superposition coding, and users decode the contents through a successive interference cancellation thereby saving energy. However this can cause interference with weaker signals when signals from stronger users are superimposed.

To enhance the speed, energy, time delay, and fairness of all devices in a network, D2D re-transmission is an optimal solution [50]. By clubbing D2D with NOMA, interference due to stronger devices can be lessened, resulting in better communication quality for weaker devices. However, there are challenges to be addressed such as encouraging relay users to share content and motivating users to buy data from relays which will be discussed in this chapter.

A device with a stronger signal can be separated from weaker signals without causing any interference, using NOMA. But NOMA communications might introduce latency. So devices closer to the source with stronger signals can decode the signals of devices that are farther away with weaker signals in the next time slot. These closer devices can positively serve as a relay if they agree to cache the offloaded content. The relaying device can then make a new combined signal and use NOMA to transmit it, through superposition coding, as shown in Figure 5.1 [7]. To maximize the quality of communication for the receiving device, this relaying process can be repeated several times [51].

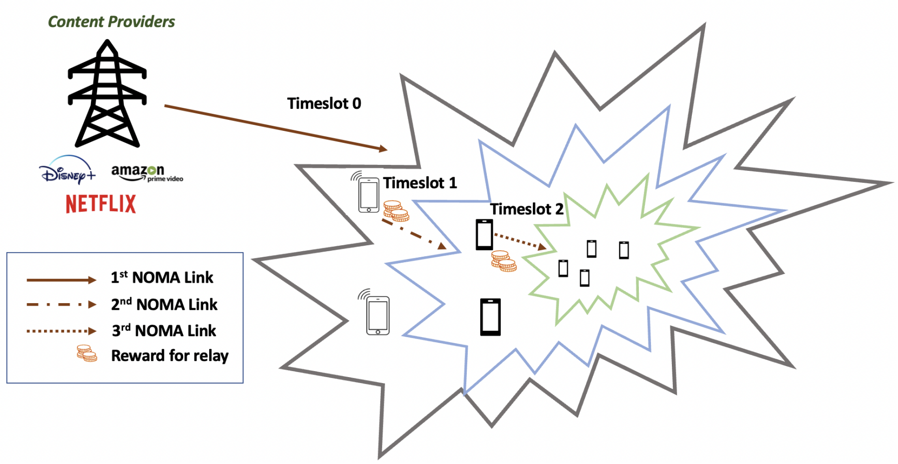

Figure 5.1: D2D retransmission enabled NOMA network

The RU must be properly driven to devote time and resources sending offloaded content to distant EUs. This chapter grants a solution in which EUs pay an additional fee for the service and have the choice to handpick a suitable relaying node from a competitive network. An auction mechanism is projected to resolve the optimal relaying node and corresponding payment, with two sealed auction schemes. This includes the first price and second price. The proposed D2D NOMA communication system provide incentive to strong EUs to partake in the auction. This is because it would be inefficient to remove content intended for longer distance users. This approach can finally lead to substantial power savings for the network.

There are several studies that investigated D2D enabled NOMA access networks [52, 53, 54]. For example, one study showed that the D2D-assisted NOMA relay augmented the Signal to Interference plus Noise Ratio for distant EUs [52]. Another study established a selection framework and bandwidth allotment technique with a combination mode to increase the D2D network performance [53]. Additionally, researchers studied the best user selection problem to boost the signal-to-interference-plus-noise ratio using a D2D enabled NOMA environment [54]. In this chapter, an alternative framework for resource allocation and relay selection in NOMA relay communications is initiated, which is based on Auction Theory and leverages incentives to drive behavior.

The EUs perform in a self-seeking and non-cooperative manner in a heterogeneous wireless network. This competitive behavior results in contests for resource allocation [55, 56]. Auctions have been widely applied for network selection and resource allocation previously, addressing problems such as competitive spectrum sharing [57], power optimization in D2D networks [58], and video traffic offloading [59]. This chapter explores the performance of auction mechanisms in a NOMA-driven D2D network for relay node selection. Earlier research on QoE-centric NOMA networks has investigated game theory-based pricing solutions [3, 8].

5.3 Utility definitions

In a NOMA network, data from the base station or content provider within a resource block are requested by the user. During the downlink transmission, the base station conglomerates all the requested content into a single superimposed signal. Users will be able to decode their own data and can also unpack data planned for farther users. Our framework allows users to formulate a new superimposed signal of content for the furthermost users and relays it during the next time slot. The farther users compensate for the relay in the retransmission. Table 5.1 list the symbols used in this chapter.

Table 5.1: Summary of notations in this chapter.

Symbol	Comments
i	List of EUs in the network. i=1,2,3,4.
j	Subset of EUs in the network. j=1,2,...i-1
$\|h_i\|^2$	Channel gain for EU_i - original transmission.
$\|h_{j,i}\|^2$	Channel gain for EU_i - retransmission from EU_j.
$\|P_i\|^2$	Power allocated by BS for EU_i.
$\|P_{j,i}\|^2$	Power allocated by EU_j for EU_i.
σ^2	Variance of the normalized AWGN.
α, β	System parameters to fine tune QoE model
χ_i	cost parameter for EU_i - original transmission
δ_i	cost parameter for EU_i - retransmission from EU_j
L	$i-th$ packet length (in bits).
B	Bandwidth
b	Modulation size

To analyze the proposed framework, we use a simple network with four EUs that makes up a NOMA wireless network, as depicted in Figure 5.2 [7].

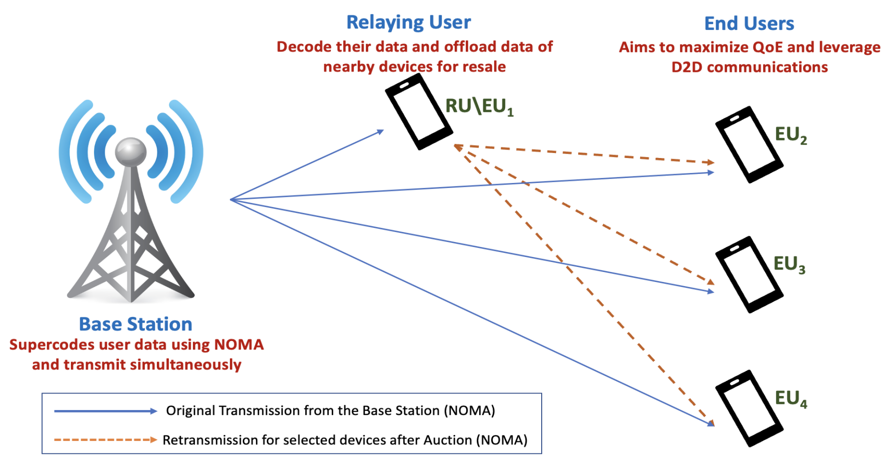

Figure 5.2: D2D enabled NOMA networks

The channel gain of EU_i is denoted by $|h_i|^2$. In order to visualize the channel better, it has been assumed that all the EU devices are arranged in order of their channel gain.

$$|h_1|^2 \geq |h_2|^2 \geq |h_3|^2 \geq |h_4|^2 \tag{5.1}$$

During time slot 0, the base station sends data to all EUs. Each EU then performs cancellation of interference to obtain their data from the received signal. The SINR gain is indicated below [3]:

$$\mathrm{SINR}_{EU_i} = \frac{P_i |h_i|^2}{\sum_{k=1}^{i-1} P_k |h_i|^2 + \sigma^2} \tag{5.2}$$

In the Equation (5.2) above, P_i and h_i^2 represent the conveyed power and gain of the channel, respectively, between the EU_i and base station. σ^2 represents the overall noise in the wireless transmission channel. The subset of user devices with higher channel gain than EU_i cause the interference and are denoted by k. Since EU_1 is the sturdiest EU in the network being projected, there is no interference and the SINR can be expressed as:

$$SINR_{EU_1} = \frac{P_1 |h_1|^2}{\sigma^2} \tag{5.3}$$

After EU_1 has decoded its own data, it can determine whether to offload the data of the farthest users. The SINR improvement for EU_1 to decode the signals of other users EU_i, where $i = 2, 3, 4$, is expressed as:

$$SINR_{EU_1,EU_i} = \frac{P_i |h_1|^2}{\sum_{k=1}^{i-1} P_k |h_1|^2 + \sigma^2} \tag{5.4}$$

EU_1, acting as the relay node, can now club the signals of farther users and transmit them during the next time slot. If EU_2 chooses not to use the relay retransmission, its utility will be limited to the SINR gain obtained from the base station, as shown in the Equation (3.5):

$$\mathrm{SINR}_{EU_2} = \frac{P_2 \left|h_2\right|^2}{P_1 \left|h_2\right|^2 + \sigma^2} \tag{5.5}$$

If EU_2 chooses to opt for the relayed data from EU_1, the SINR gain would vary. The expression for SINR gain with relayed data is given by Equation (5.6). Here, EU_2 is the user with higher channel gain for relayed data and hence there will not experience any interference present in the newly transmitted data arriving from relay user.

$$SINR_{EU_2} = \frac{P_2 \left|h_2\right|^2}{P_1 \left|h_2\right|^2 + \sigma^2} + \frac{P_{1,2} \left|h_{1,2}\right|^2}{\sigma^2} \tag{5.6}$$

The expression above uses $P_{1,2}$ to denote the power that EU_1 assigns for retransmission and $|h_{1,2}|^2$ to represent the channel gain between EU_1 and EU_2. It represents the SINR gain for EU_2 when it decides to buy the retransmitted data from EU_1. This general equation for SINR of user i when EU_1 serves as the relaying user is based on previous research in [51].

$$\mathrm{SINR}_{EU_i} = \frac{P_i \left|h_i\right|^2}{\sum_{k=1}^{i-1} P_k \left|h_i\right|^2 + \sigma^2} + \frac{P_{1,i} \left|h_{1,i}\right|^2}{\sum_{l=2}^{i-1} P_{1,l} \left|h_{1,i}\right|^2 + \sigma^2} \tag{5.7}$$

The SINR gain of user i can be increased appreciably when the remaining $(N-1)$ users are decoding the weaker user signals and relaying them in the concurrent $(N-1)$ time slot. In general, the set of users that cause intrusion during retransmission is represented by l. As an example, the SINR gain for EU_4 is written as Equation (5.8).

$$\mathrm{SINR}_{EU_4} = \frac{P_4 \left|h_4\right|^2}{\sum_{k=1}^{3} P_k \left|h_4\right|^2 + \sigma^2} + \frac{P_{1,4} \left|h_{1,4}\right|^2}{\sum_{l=2}^{3} P_{1,l} \left|h_{1,4}\right|^2 + \sigma^2} + \frac{P_{2,4} \left|h_{2,4}\right|^2}{P_{2,3} \left|h_{2,4}\right|^2 + \sigma^2} + \frac{P_{3,4} \left|h_{3,4}\right|^2}{+\sigma^2} \tag{5.8}$$

where $P_{1,4}$ and $|h_{1,4}|^2$ denote the power allocated by EU_1 for retransmission and gain for the transmission link between EU_1 and EU_4. Additionally, $P_{2,4}$ and $P_{3,4}$ represent the power allocated by users EU_2 and EU_3 for the retransmission service, respectively, and $|h_{2,4}|^2$ and $|h_{3,4}|^2$ denote the corresponding channel gains.

In this chapter, it is assumed that there is only one relaying user (EU_1) in the NOMA network as shown in Figure 5.2. However, the equations and solutions derived can be applied to networks with multiple levels of relaying without significant changes.

5.3.1 Utility definition of user

The measure of user satisfaction can be described based on the per-session QoE and the cost acquired to get the desired service. The QoE attained can be articulated as a two-level log function of the allotted resources [25]. The mathematical model for calculating the QoE is:

$$QoE_{EU_i} = \alpha \log_2 \left(1 + \beta \log_2 \left(1 + SINR_{EU_i}\right)\right) \tag{5.9}$$

The user EU_i has two types of expenses: the cost paid to the base station denoted by χ_i to acquire the transmission, and the cost paid to the relaying device denoted by δ_i to acquire service. However, the strongest user EU_1/RU does not have the relaying cost. The final utility gain of the mobile user is defined as the total gain in quality minus the costs paid.

$$Utility_{user} = U_{EU_i} = QoE - \chi_i P_i - \delta_i P_{1,i} \tag{5.10}$$

The variables P_i and $P_{1,i}$ refer to the allotted power by the base station and the relaying user RU for user EU_i, respectively. It is assumed in this paper that users do not have any control over the cost χ_i and power P_i set by the base station. To improve their utility, users can compete with other users to obtain the best possible relaying service at the optimal price. The maximization problem for both the buyer and seller user is to compute the appropriate bid δ that maximizes their overall utility U_{EU_i}.

5.3.2 Utility definition of the relay

The system permits sturdier EUs to act as relays for users who are remoter and require extra D2D transmission service. In this system, the utility of the relay is derived from the EUs that require added D2D transmission service to increase their QoE. To clarify the system's operation, we use a concise demonstration with only four EUs, and we assume that only the strongest user EU_1 acts as the relay (RU). In this chapter, we consider only for one round of retransmission. Subsequent retransmission will result in having supplementary summation terms in the utility definition.

$$\psi_{RU_i} = \lambda_i \frac{LP_{1,i}}{bB} \tag{5.11}$$

The cost of transmission for the relay, denoted as ψ_{RU}, refers to the cost of transmitting a packet over the NOMA channel per unit of energy. This cost is computed by using the frame size L (in bits), power of transmission per bit $P_{1,i}$ (in watts) for user i, modulation scheme constellation size b, and allocated spectrum B. Additionally, λ represents the price value per unit of energy consumed by the user i.

$$Utility_{RU/EU_1} = \sum_{m=2}^{N} \delta_m P_{1,m} - \sum_{m=2}^{N} \lambda_m \frac{L P_{1,m}}{bB} \tag{5.12}$$

The relay's goal is to choose the set of users farther away (via auction - winners) and provide them with retransmission services in a way that maximizes their utility. Here, m refers to the set of users, including EU_2, EU_3, and EU_4, who have decided to obtain the retransmission service through the relay.

5.4 Auction-theoretic solution

In this chapter, two auction schemes are offered to determine the best solution for the NOMA D2D relaying problem, which is described as the cost user is ready to spend and the power relay is comfortable to provide for the service. The auction setting comprises bidders $i = 1, 2, 3..., n$ (in this case, the weaker EUs) and one object to be sold, which is the retransmitted data.

To elucidate further, in a sealed auction, each bidder's valuation and information about the object being sold are kept private from other bidders. In this case, each weaker EU participating in the auction would autonomously determine their own valuation for the retransmission service based on their own QoE requirements, budget constraints, and network conditions. The valuation of one bidder does not disturb the valuation of another bidder.

The list of events during an auction are:

Step 1: The EUs scan the channel to determine the channel gain and interference.

Step 2: In the beginning of the auction, the relay announces their capacity C in terms of power available for allocation and list of data available for retransmission.

Step 3: Each user EU interested in obtaining service during the next time slot places bid to the relay.

Step 4: The auction ends and the RU announces the winner / set of winners.

Step 5: The amount to be paid is computed based on the auction dynamics and the demand is revealed (that is, information needed for EUs to determine whether to offload data during next relay's retransmission).

5.4.1 First price sealed-bid auction

One normally used method of auctioning is the first price sealed-bid auction (FPSBA), typically known the blind auction. Under FPSBA, all bidders propose their bids concurrently in sealed envelopes. Highest bidder triumphs the auction and pays the amount they submitted as their bid [60].

Computation of the valuation:

Using backward induction technique, the actual estimation of the retransmission service is computed. Concavity of the user's utility function U_{EU_i} with respect to the power transmitted can be shown by calculating the second-order derivative of Equation (5.10) as elucidated below as Equation (5.13).

$$\frac{\partial^2 U_{EU_i}}{\partial P_{1,i}^2} = -\frac{\alpha\beta \cdot (\beta \ln (SINR_{EU_i} + 1) + \beta + 1)}{(SINR_{EU_i} + 1)^2 \left(\beta \ln (SINR_{EU_i} + 1) + 1\right)^2} \tag{5.13}$$

The expression in Equation (5.13) is negative for all values of the variables involved, since the numerator terms α, β, and $SINR$ are positive, and all the terms in the denominator are squared. To determine the valuation v_i that provided the best utility of the client, the first derivative is set to zero. This results in Equation (5.14).

$$v_i = \delta_i = \frac{\alpha\beta}{(SINR_{EU_i} + 1)\left(\beta \ln\left(SINR_{EU_i} + 1\right) + 1\right)} \tag{5.14}$$

Computation of the bid:

After determining the valuation of the retransmission service, the EU must choose on the amount they are ready to pay if they win the auction, while bearing in mind the trade off between the probability of winning and the amount paid. It's imperative to note that there is no prevailing strategy for the bidders. The Nash Equilibrium solution for the sealed first price auction is given by theorem 1.

Theorem 1: In FPSBA with two risk-neutral bidders whose valuations, v_1 and v_2, the random variables are drawn independently and identically from a uniform distribution $U(0,1)$ with weights $(1/2)v_1$ and $(1/2)v_2$. This is the bases Nash equilibrium strategy profile [61].

Proof: Assume that the $bidder_2$ bids $1/2v_1$ based on the theorem above and $bidder_1$ bids arbitrary $s1$. Then, $bidder_2$ wins every time when $s_1 < 1/2v_1$ and loses otherwise. The expected utility for the $bidder_1$ can be computed as:

$$
\begin{aligned}
E\left[bidder_1\right] &= \int_0^{2s_1} \left(v_1 - s_1\right) dv_2 + \int_{2s_1}^{1} (0) dv_2 \\
&= \left(v_1 - s_1\right) v_2 \Big|_0^{2s_1} \\
&= 2v_1 s_1 - 2s_1^2
\end{aligned}
\tag{5.15}
$$

The best response for $bidder_1$ to $bidder_2$'s strategy is computed by taking the first order derivative of Equation (5.15) and equating it equal to zero.

$$
\begin{aligned}
\frac{\partial}{\partial s_1}\left(2v_1 s_1 - 2s_1^2\right) &= 0 \\
2v_1 - 4s_1 &= 0 \\
s_1 &= \frac{1}{2} v_1
\end{aligned}
\tag{5.16}
$$

As a result, if $bidder_2$ bids exactly half of their valuation, then the optimal bidding strategy for $bidder_1$ is to bid half of their own valuation as well. The same reasoning applies to the optimal bid for $bidder_2$, since the game is symmetric [61].

The Nash Equilibrium solution derived can easily be extended to a multiplayer auction based on Lemma 3.

Lemma 3: For the case of n risk-neutral agents playing the FPSBA game, where each agent's valuation is an independent and identically distributed random variable drawn from a uniform distribution on the interval [0,1], the unique symmetric equilibrium is characterized by a strategy profile in which each agent bids $\frac{n-1}{n}$ times their own valuation. Thus, the equilibrium bidding strategy for each agent i is $(\frac{n-1}{n})v_i$, where v_i is the valuation of agent i.

Therefore, the Nash Equilibrium bid for the users EU_2, EU_3 and EU_4 in our proposed system model for relaying service by RU will be 2/3 $v2$, 2/3 v_3 and 2/3 v_4 respectively.

5.4.2 Second price sealed-bid auction

Under SPSBA, participants present bids built on their valuations, without being mindful of the other bidders' offers. The peak bidder is declared the winner, but only pays the second highest bid amount. The Vickery-Clarke-Groves (VCG) mechanism, which was inspired by the Vickery-score auction [62], is used as the second-price auction game. The VCG auction is outstanding in that it pledges the accurate valuation of each bidder's object because of its weakly leading strategy property, as described in reference [63].

Computation of the bid:

The SPSBA VCG auction functions on the following bidding rules. The VCG mechanism is considered to be effectual, and all participants have a dominant strategy to announce their genuine valuation (that is, truthfully stating $v_i = \delta_i$ is the optimal strategy regardless of other bidders' declarations). When they follow this strategy, the VCG mechanism implements the efficient outcome. We will analyze this in two scenarios.

case 1: bidder$_i$ wins with the auction by announcing v_i and pays $\mathcal{C} < v_i$

In this auction, the bidder who wins is obligated to pay a price which is lesser in comparison to their own bid. Accordingly, there is no incentive to either increase or decrease the bid. However, if the bidder's offer drops below that of the second-highest bidder, they will lose the auction.

case 2: bidder$_i$ loses with the auction by announcing v_i and pays nothing

Since the winning bidder is still mandated to pay an amount even if their bid is lower than their actual valuation, there is no incentive for them to lower their bid anymore. Instead, if the bidder goes beyond the highest bid, they will end up paying more than the actual valuation, which is not useful. Therefore, truth-telling is considered the most dominant strategy.

VCG auction mechanism:

Step 1: The efficient outcome of VCG mechanism for the NOMA relaying service auction is a Groves mechanism $(x^*, \mathcal{C}_i(v))$ given by

$$x^* = \arg\max_x \left\{ \sum_i v_i(x) \right\} \tag{5.17}$$

where x^* denotes the socially efficient action.

Step 2: The total welfare of the society, not counting the bidder EU_i is computed as

$$\sum_{j \neq i} v_j\left(x^*\right) \tag{5.18}$$

Step 3: The change to this welfare if the bidder EU_i is not part of the society (community of bidders) is then calculated as

$$x^*_{-i} = \arg\max_x \left\{ \sum_{j \neq i} v_j(x) \right\} \tag{5.19}$$

Step 4: The measure of how much the bidder EU_i contribute to the rest of the society is then computed (may be negative).

$$\mathcal{C}_i(v)) = \sum_{j \neq i} v_j\left(x^*\right) - \sum_{j \neq i} v_j\left(x_{-i}^*\right) \tag{5.20}$$

where $\mathcal{C}_i(v)$ denotes the amount of money paid by the auction winners and it is also the cost of individual bidders.

5.4.3 Numerical example

Table 5.2 presents the valuation of the relaying service from RU for EU_2, EU_3, and EU_4. Since EU_2 is the nearest user, they are only able to choose the highest power option with no interference. EU_3 has the option to pay more for the best power option with no interference or pay slightly less for power option 2. Finally, EU_4 has the flexibility to select from three power options, namely being the closest and only user with high power, the second user with lesser power (power 2), or the third user with even less power (power 3 - which results in more interference).

Table 5.2: Illustration : An Example of VCG Auction

	EU_2	EU_3	EU_4
$Power1$	2	3	5
$Power2$	-	2.5	4
$Power3$	-	-	3

Step 1: Since the sum of bids from all three users $(2 + 2.5 + 3)$ is greater than the sum of the first and the second highest bid $(3 + 4)$, the relay will choose to provide service to all three users. In other words, the relay will select to service all the users as the combined bid of all three users is the highest among all the bids.

Step 2: Cost for EU_2: The cost is computed ignoring EU_2 = 3+4 = 7. With EU_2 in the society, the money from other users is 2.5+3=5.5. The EU_2 pays 7-5.5=1.5. Similarly cost of EU_3 and EU_4 can be computed as 1 (5-4) and 2 (4.5-2.5).

Step 3: The RU provides retransmission for all the three users for prices \$1.5, \$1 and \$2 respectively; earning a total of \$4.5

In contrast, if FPSBA were employed, the solution would be 2/3 of the v_i value. Thus, the winning bids for EU_2, EU_3, and EU_4 would be $2/3 \times 2$, $2/3 \times 2.5$, and $2/3 \times 3$, respectively. The overall cost borne by the users to receive the same service using the first price auction would be 4.9999. Therefore, the previous example shows that the user can attain higher utility using SPSBA.

5.5 Numerical analysis

Simulations were performed to assess the functioning of the NOMA Relay network with both the FPSBA and SPSBA. The channel gain $|h_i|^2$ ranged from 0 to 40 dB. The power of transmission P and the power of noise σ^2 were in the range of 10 to 30 dBm and 1 to 5 dBm, respectively. The data rate B was set at 20 Mbps and the data length L was set at 300 Mbits. The system parameters α and β were set to 1 and 10, respectively.

The revenue of the relay is established as a concave function in Figure 5.3 [7] in relation to total number of user devices supported in relay retransmission. The rise in the number of users causes interference, resulting in lower bids from users. Therefore, the relay can maximize its utility by selecting the appropriate combination (subset) of users. It is worth noting that the SPSBA VCG auction provides considerably better utility for the relay, irrespective of the total user serviced.

The Figure 5.4 [7] illustrates effect of various channel gains on the SINR gain of the user equipment (UEs). In this simulation, the assumption is that only the downlink channel in between the RU and BS vary, i.e., if the RU moves closer to the BS, the gain of the channel $|h_1|^2$ increases, while the gains of the channels between the three EUs remain unchanged, i.e., $|h_{1,2}|$, $|h_{1,3}|$, and $|h_{1,4}|$ are constant. The results reveal that as the channel gain increases

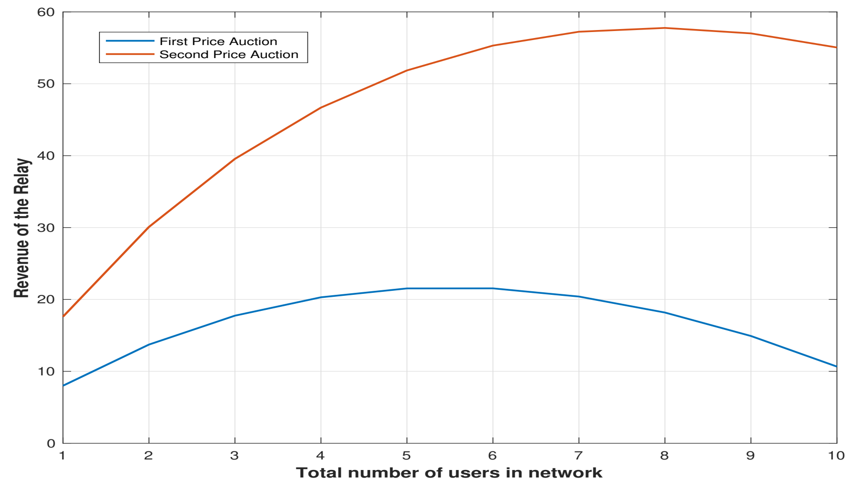

Figure 5.3: Utility of Relay for both auction schemes.

across the EUs, the SPSBA (VCG) produce better results in terms of the SINR gain of the EUs. The figures 5.3 and 5.4 together demonstrate that the VCG auction can be leveraged to attain higher utility for EUs and the RU.

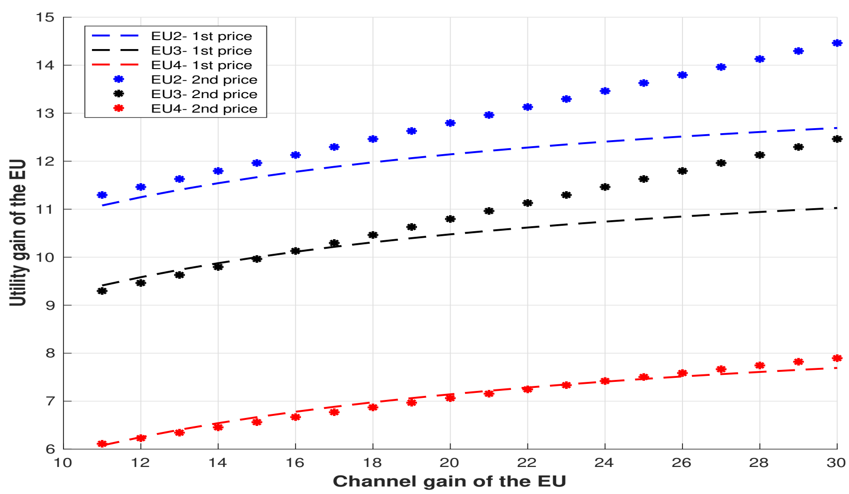

Figure 5.4: Utility of Relay for both auction schemes.

Figure 5.5 [7] compares the QoE for EU_2 with and without the extra retransmission from RU. As mentioned earlier, the QoE is a concave function, which can be envisaged from the figure. With the retransmission, the $SINR_{EU_2}$ is enhanced by an additional term of $\frac{P_{1,2}|h_{1,2}|^2}{\sigma^2}$, resulting in a higher QoE. It can also be perceived that the EUs' participating in the relay retransmission can achieve higher QoE at lower transmission power levels. This implies that the proposed framework can ideally benefit the base station by reaching higher spectral efficiency.

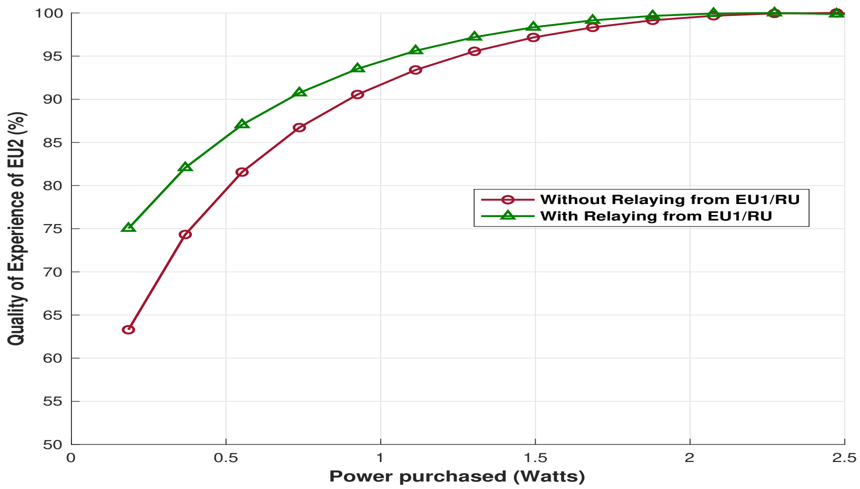

Figure 5.5: Comparison of QoE with and without D2D

5.6 Concluding remarks

This chapter introduced a novel framework for using NOMA relay to save power compared to direct retransmission from the base station. The framework by auctioning transmission power incentivizes short distance users to act as relays. The optimal solution was found using two auction techniques, FPSBA and SPSBA (VCG). The results confirmed that all three parties benefit from the proposed scheme and that VCG auction outpaces FPSBA in optimal networks with good channel gain and minimal interference. Largely, the proposed framework has the prospective to upturn spectral efficiency and increase for end users in NOMA networks.

Chapter 6

Orthogonality Centric Pricing: Resource Management in Hybrid NOMA-OMA Networks

6.1 Background

The current service used in wireless content transmission is OMA. An extension to that called NOMA is a novel solution for curbing the traffic congestion and latency in next-generation wireless multimedia services. Although OMA has its own disadvantages, it is predicted that it will also exist alongside NOMA in the coming times. A wireless access pricing framework that incorporates the philosophy of Uber/Lyft ridesharing in introduced for NOMA-OMA hybrid network. This model is described on ”orthogonality-centric” design that considers

The materials presented in Chapter 6 have been presented at the 2022 IEEE International Conference on Communications (ICC) [8] and the 2023 IEEE Wireless Communications and Networking Conference (WCNC) [9] the variances in shared NOMA and exclusive OMA access rates in wireless networks. The proposed framework employs incentives to urge the transfer of data content from an OMA link to a NOMA link. Therein our main aim is to enhance user's Quality of Experience (QoE) and base station's revenues simultaneously. However, it will be a challenge to effectually distribute data between the available NOMA and OMA links to reach ideal service. To resolve this, OMA can be utilized for transmission of essential frames. Finally, game theory methods were utilized to acquire a solution that accomplishes the Nash Equilibrium

6.2 Introduction

Orthogonal Frequency Division Multiple Access (OFDMA) is a type of multiple access scheme that allots discrete sub-band frequencies that are orthogonal to each other to diverse users for accessing the network. Although there are many such schemes we are still faced with the challenge of fast increase internet-ready devices and users. Hence innovative technologies in cellular communications are essential to meet these demands [64]. One such technology is NOMA and it is being widely investigated. The reported finding from the studies project NOMA as a suitable paradigm to handle the ambitious data requirements of beyond 5G networks [10].

NOMA follows a strategy distinct from the conventional OFDMA or OMA schemes. It allows support for additional users than the number of available orthogonal resource slots by non-orthogonal resource allocation [65]. However, one critical problem is the residual interference that occurs due to channel estimation and decoding errors. Also, the Inter-Block Interference (IBI) can act as a significant challenge to mobile device performance in a multi-resource block NOMA network [8]. To tackle these problems, a hybrid NOMA-OMA multiple access technology for the next generation of wireless communications has been proposed recently [64].

The utilization of a NOMA-OMA hybrid network presents some obstacles that need to be addressed. One such difficulty is the implementation of strategic power allotments and resource rationing for signal recovery. Additionally, in order to enhance the QoE of mobile users, which is a critical component of resource allocation in wireless systems, an appropriate approach must be adopted [27]. Another challenge is the efficient delivery of traffic by base stations among the available NOMA/OMA resource blocks while simultaneously improving network profits [2]. To address these issues, a ridesharing-inspired QoE-driven pricing scheme called Orthogonality Centric Pricing (OCP) has been proposed in this chapter. A block diagram depicting the corresponding OCP pricing architecture is displayed in Figure 6.1 [8].

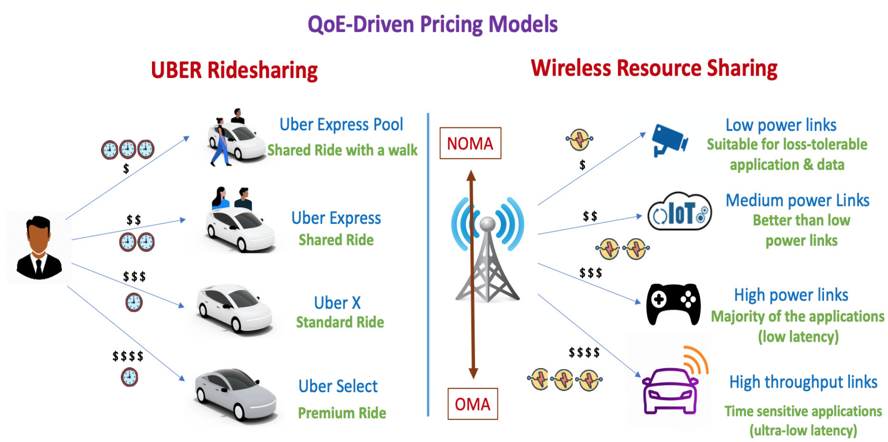

Figure 6.1: QoE Pricing Schemes: Analogous Uber pricing model and proposed orthogonality centric pricing for NOMA/OMA hybrid network.

QoE-driven pricing mechanisms have grown extensively in various applications including airline seat selection and Uber ridesharing. For example, Uber provides four choices to its customers. The cheapest one, Uber Express Pool, is a shared ride from a mutual pickup location. The subsequent cheapest option, Uber Express, is also a shared ride, except for the customer being able to pick the pickup and drop-off locations. The most prevalent choice is the standard Uber X, which offers a private ride. Uber also offers a premium experience with Uber Select. These services come in different rates, and the customers can pick their desired option liberally. This suggests that pricing algorithms can be developed to guarantee profits irrespective of the customer's preference and ensure satisfactory QoS. In this chapter, a QoE-driven pricing approach for future wireless multiple access networks is introduced.

Certain applications have a higher error tolerance such as video surveillance and remote sensing. This is in comparison to applications such as self-driving cars and live multimedia streaming. The key concept of the established OCP scheme is to tactically distribute the available resources based on the end-user application and QoE requirements. Their CSI and demand will determine the rates of the available links. Herein, customers will have the freedom and the best value for their money by being able to select the link(s) they are interested in buying at a given rate. In this chapter, game theory was applied to validate that the proposed pricing model can profit both the base station and the customer evenly.

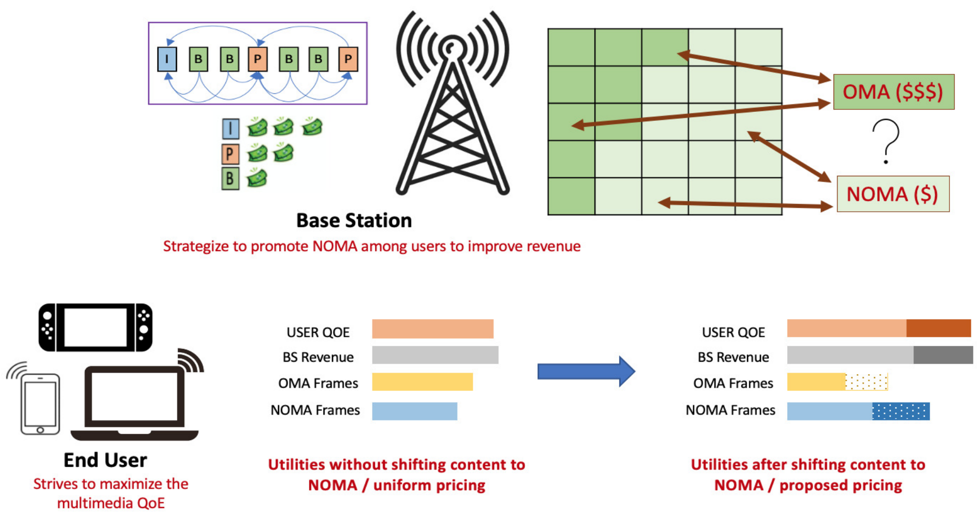

Figure 6.2: Illustration of multimedia data transmitted over NOMA/OMA hybrid network

About 60% of all internet traffic is generated by multimedia applications that involves streaming and interactive gaming from mobile devices [66]. This multimedia data transmitted over the wireless channel after compressing by an appropriate encoding technique. One such technique is the High Efficiency Video Coding (HEVC), also known as H.265. It is the most sophisticated standard that splits content into I-frames (Inter frames), P-frames (forward-predicted frames), and B-frames (bi-directionally predicted frames). The I-frames are vital frames and can be conveyed through the OMA link in a hybrid NOMA-OMA network to conflict Inter-Block Interference (IBI). The P-frames and B-frames can also be transmitted using the NOMA link but are smaller frames of lower quality that depend on I-frames. The multimedia communication in a hybrid NOMA-OMA network is portrayed in Figure 6.2 [9] above.

The main advantage of hybrid NOMA-OMA network is that it permits the base station to serve more users concurrently, thereby increasing its gain. Here the base station will urge the customers to shift their data to the NOMA resource blocks for even higher network capacity. By doing so, concerns will be raised about compromising their QoE. This chapter offers an incentivizing pricing framework that persuades users to move their content by letting the base station to charge the resource blocks based on noise, interference, and available power, as well as setting unequal prices for I, P, and B frames. The customer can choose which resource block to occupy and how much I, P, and B frames to secure to satisfy their utility.

The NOMA-OMA hybrid model is suitable for assisting massive Machine Type Communication (mMTC) in ultra-dense networks [64]. Some studies have also evaluated its performance [67] and optimizing latency [68] in hybrid transmission. Moreover, the relay selection issue in cooperative hybrid networks has also been investigated [69]. But, optimizing the QoE and designing novel pricing schemes for hybrid network is still unexplored.

Service providers have made several changes in their pricing strategies to satisfy the QoE requirements of customers. Smart data pricing [70] and smart media pricing [21] are ways to subjectively measure QoE by assuming price as a resource. Although still in inquiry, some studies that proposed strategic pricing for NOMA resources include Price-Based Resource Allocation in NOMA System with Hardware Impairments [71], Interference-driven pricing for NOMA Fog networks [72], and Game theory-driven pricing metrics for cognitive radio NOMA [73]. This chapter is focused on building a new approach that achieves joint QoE-Profit maximization in a hybrid NOMA/OMA network. To do this, a pricing model is proposed that would promote leveraging NOMA resource blocks in a NOMA-OMA hybrid network.

6.3 NOMA/OMA hybrid system model

The diagram depicted in Figure 6.2 [9] illustrates the interaction between the user and the gaming service provider in a hybrid NOMA-OMA network. In this type of network, it is assumed that the user would purchase only a portion of the data using OMA, and the remaining data would be transmitted over NOMA. It is suggested that the user should purchase the most important content over the OMA link to mitigate the impact of inter-block interference and retransmission delay, while less important content can be purchased over the NOMA link. However, this method of dividing the content is not necessarily ideal among the users and provider.

The available resources at the base station are divided into NOMA and OMA blocks in both time and frequency domains. In the NOMA-OMA pricing model, the base station determines the cost per bit of transmission on-the-fly for each resource block in the network. Because the OMA link is a dedicated link to a single user, the cost to the user for occupying a single OMA block is significantly higher than that for occupying a NOMA block, which is shared among multiple users. Additionally, the cost per bit of an I frame is higher than that of a P or B frame, motivating the user to shift some of the content from OMA to NOMA blocks. Such a shift would also increase the network capacity, benefiting the base station. The developed model is shown in Figure 6.3 [9].

6.3.1 Utility definition of base station

The allocation of prices by the base station for different resource blocks is a fundamental factor of the proposed model. To simplify, the cost for all OMA blocks is assumed to be y_{oma}, while the cost for all NOMA blocks is uniformly set to y_{noma}. These rates represent the per-bit cost for transmitting multimedia content using OMA and NOMA, respectively.

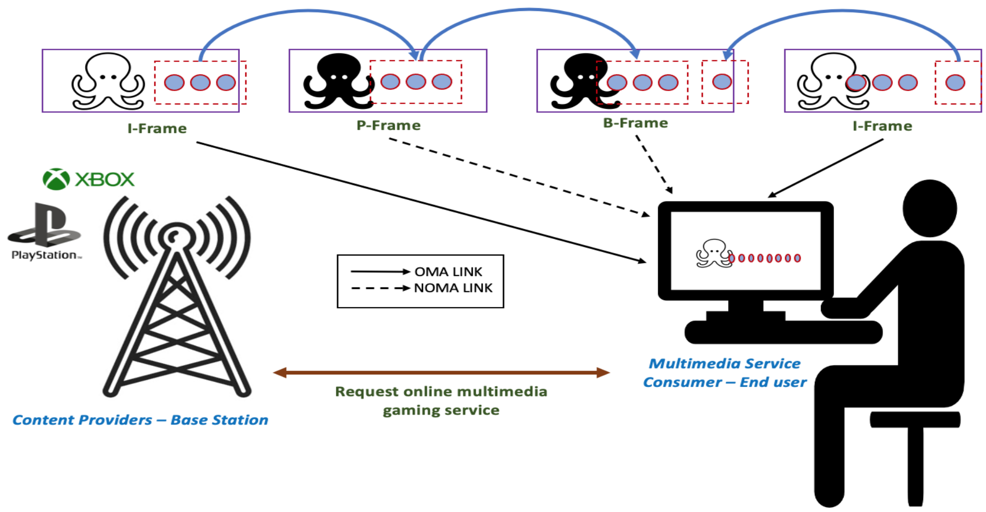

Figure 6.3: NOMA/OMA hybrid system model

To evade traffic congestion and interference, it is helpful to assign higher prices to OMA blocks, which are exclusively allotted to individual users. Moreover, the base station may allot additional communication resources to meet the QoE requirements of OMA traffic, which would cost more.

The revenue generated by the base station can be classified into three parts: revenue from scheduled NOMA service priced at y_{noma}, revenue from scheduled OMA service priced at y_{oma}, and additional revenue obtained by encouraging users to switch from OMA to NOMA service, priced at $y_{oma2noma}$. For users to be motivated to shift their service from OMA to NOMA, it is vital to offer them a compelling reason.

$$S = S_{oma} \cup S_{oma2noma} \cup S_{noma} = \sum l \tag{6.1}$$

The function that calculates the utility of the base station can be expressed by using the indices i and j, where i represents the user index and j represents the multimedia packet index. The utility function of the base station can be determined by taking the total revenue generated from all users and subtracting the communication costs incurred in both OMA and NOMA blocks.

$$U_{BS} = y_{noma} \sum l_j\big|_{j\{S_{noma}} \cup s_{\text{oma2noma}} \quad + y_{oma} \sum l_j\Big|_{j\{s_{oma}\}} - C_{noma} \sum l_j\Big|_{j\{s_{noma} \cup s_{\text{oma2noma}}\}} \\ - C_{oma} \sum l_j\Big|_{j\{s_{oma}\}} \tag{6.2}$$

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

The optimization problem that the base station needs to solve is to determine the cost of the NOMA resource block, denoted by y_{noma}, which would result in an increase in $S_{oma2noma}$ while maximizing the utility function.

6.3.2 Utility definition of the mobile user

The mobile user sends requests for multimedia data, S_{oma} and S_{noma}, via the OMA and NOMA links, respectively, to the base station. To quantify the user's QoE, a comprehensive QoE model can be employed, which considers various parameters such as the user's personal preferences for the multimedia content (γ), the packet error rate (P_k), and the gain in multimedia quality (q_j). This QoE model can be expressed mathematically using the following equation.

$$QoE = \frac{a_1}{1 + e^{-a_2 \sum_{j=1}^{M} q_j \prod_{k \epsilon \pi j} (1-P_k) + a_3 \gamma + a_4}} \tag{6.3}$$

The quality of multimedia content received by the user can be improved by reducing the distortion in each multimedia packet, which can be quantified as the multimedia quality gain q_j. The packet error rate of the k^{th} packet is denoted by p_k, and π represents the decoding dependency set of the packet. The total number of packets purchased by the user is denoted by M. The equation that models the QoE achieved by the user takes into account the user's personal preference for the multimedia content (γ), the packet error rate (p_k), and the multimedia quality gain (q_j). In previous research [28], the values of the system parameters were set to $a_1 = 3.8$, $a_2 = 4.9$, $a_3 = 3.6$, and $a_4 = 3.5$ based on empirical studies. These parameters can be adjusted and fine-tuned during implementation to optimize performance. The packet error rate p_k depends on the data length and the bit error rate, and can be expressed as a function.

$$P_k = 1 - (1 - BER)^{l_k} \tag{6.4}$$

The bit error rate (BER) in the NOMA resource blocks can be approximated using the desired multimedia packet signal-to-noise ratio (SNR) [4]. The transmitted power is denoted by P_t, and the channel gain between the user and the base station is represented by h. The power of the noise in the communication channel is given by $R_s N_o$.

$$BER = \frac{2}{b}\left(1 - \frac{1}{2^{\frac{b}{2}}}\right) \mathrm{ERFC}\left(\sqrt{\frac{3}{2\left(2^b - 1\right)} \frac{P_t|h|}{\sum_{g=1}^{N-1} P_g|h_g|^2 + R_s N_0}}\right) \tag{6.5}$$

The set $g(0, 1, 2, ..., N-1)$ represents the users in the NOMA resource block who are closer to the base station than the end-user N, causing inter block interference to the end user's data. Conversely, in the case of OMA links, the user purchasing data does not face any interference from other users.

$$\sum_{g=1}^{N-1} P_g \left|h_g\right|^2 = 0 \tag{6.6}$$

The user's utility function takes into account both the QoE gain and the cost paid to the service provider. Specifically, the user pays a price of y_{noma} for each bit of data transmitted over the NOMA link and a price of y_{oma} for each bit of data transmitted over the OMA link. The overall utility for the user can be expressed as the difference between the QoE gain and the total cost incurred, as shown below:

$$U_{user} = QoE - y_{noma} \sum l_j \Big|_{j\{S_{noma} \cup s_{\mathrm{oma2noma}}} - y_{oma} \sum l_j \Big|_{j\{S_{\mathrm{oma}}\}} \tag{6.7}$$

$$st.\ U_{user} \geq 0$$

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

The optimization problem for the user is to find the optimal distribution of the total amount of data l_j between the OMA and NOMA links while satisfying the data length constraints. The minimum and maximum data lengths required for meaningful encoding of multimedia data are represented by l_{min} and l_{max}, respectively.

6.4 Game-theoretic analysis

Nash equilibrium is defined as the circumstance in a game where each player picks their best strategy, given the strategies selected by the other players [2]. Here, the game is amongst the service provider and the consumer, who both intend to maximize their own utility. By attaining a Nash equilibrium, the optimal pricing strategy for the service provider and the optimal data allocation strategy for the user can be derived. This should produce a stable outcome where neither player has an enticement to diverge from their strategy.

The total number of bits required to transmit the requested multimedia file is given by $L = \sum l_j$. The frames that the user must purchase over the OMA link can therefore be obtained as

$$\sum l_j \Big|_{j\{S_{oma}\}} = L - \sum l_j \Big|_{j\{S_{noma} \cup S_{oma2noma}\}} \tag{6.8}$$

Thus, the aim of the user can be simplified to calculate the total quantity of NOMA bits that can be procured at the base station's set price. After this, the remaining bits can be bought using OMA. Consecutively, we assume that the cost of the OMA resource block y_{oma} would be kept fixed by the base station while y_{noma} can be adjusted. To achieve maximum profit, we formulate the optimization problem as a game and then calculate the Nash Equilibrium solution $\left\{y^*_{\text{noma}}, l^*_j\right\}$.

The Stackelberg game is an extensively used strategic game in economics, where a leader firm takes the first move, followed by consecutive moves of follower firms. In the previous chapter [2], a two-stage Stackelberg game was used to derive the Nash Equilibrium solution. In the current case, the interaction between the base station and the user can be modeled using a Stackelberg game. However, to apply the Stackelberg game, the utility equations need to be concave, which is arduous to prove for equations (6.3) and (6.8). Thus, the generalized best response game was utilized to gain the solution.

To obtain the best response game theoretic solution, a technique known as Iterated Elimination of Strictly Dominating Strategies (IESDS) can be used. This technique involves simplifying the game by eliminating the strategies that the players will never choose, resulting in at least one set of solutions for both players [41]. To implement IESDS, a two-dimensional table is created with discrete values within the acceptable range for service cost y_{min}, y_{max} and data length l_{min}, l_{max}. The table is then populated by evaluating equations (6.3) and (6.8).

Step 1: Best response game - user's perspective

For each row in the table representing a specific price set by the base station, the user calculates the data length that maximizes their utility and selects the corresponding cell in that row as their optimal response. This process results in the user selecting a single cell in each row of the table as their strategy for the given range of prices.

Step 2: Best response game – base station's perspective

Step 1 is replicated for the base station, but instead of varying the price, the different data length combinations available to the user are considered (represented by the columns in the table). For each column, the base station determines the price that maximizes its own utility. Therefore, the base station selects one cell in each column as the optimal response to that particular data length.

Step 3: Mutual best response

The mutual best response of the game can be defined using the definition below.

Definition 1: *Optimal solution in a best response game is the strategy set* $\left\{y^*_{noma}, l^*_j\right\}$ *that produces the greatest payoff given all other game strategies, such that* $U_{user}\left(y^*_{noma}, l^*_j\right) > U_{user}\left(y^*_{noma}, l_j\right)$ *and* $U_{BS}\left(y^*_{noma}, l^*_j\right) > U_{BS}\left(y_{noma}, l^*_j\right)$.

To simplify, we search for the cells in the table where both the user and base station have selected as their best response. These cells are considered best solutions and can be used by both players to achieve their optimal utility.

When applying IESDS, it is common to find that there are no mutual best responses between the players. In such cases, a Pure Strategy Nash Equilibrium (PSNE) solution cannot be obtained. However, a Mixed Strategy Nash Equilibrium (MSNE) solution can be derived. This involves determining a set of probabilities with which the players should mix their strategies, such that the other player becomes indifferent between their pure strategies. To illustrate this, consider Table 6.1 below, which has a different set of utilities.

Table 6.1: Example utility matrix for MSNE analysis

	$L_1 = 1 * 10^9$ $Iframes$	$L_2 = 1 * 10^7$ $IPframes$	$L_3 = 1 * 10^5$ $IPBframes$
$Y_1 = 3$	(13, 13)	(10, 14)	(10, 10)
$Y_2 = 2$	(12, 15)	(11, 11)	(12, 10)
$Y_3 = 1$	(5, 0)	(5, 0)	(10, 10)

Step 4: Apply IESDS to reduce the utility matrix

The table presented above demonstrates that for all values of L, the price $Y_2 = 2$ provides a higher payoff than $Y_3 = 1$. As a result, selecting Y_2 would always be a better option for the OU, and Y_3 would never be chosen. Therefore, the row for Y_3 can be eliminated from the table. Similarly, column L_3 can be eliminated as L_2 is a better strategy for the OU than L_3. Thus, the initial table has been reduced to a table as displayed below. The best responses of both the EU and OU have been identified and underlined.

Table 6.2: Example utility matrix for MSNE analysis - reduced

	$L_1 = 1 * 10^9$ $Iframes$	$L_2 = 1 * 10^7$ $IPframes$
$Y_1 = 3$	($\underline{13}$, 13)	(10, $\underline{14}$)
$Y_2 = 2$	(12, $\underline{15}$)	($\underline{11}$, 11)

Step 5: Determination of Mixing Probabilities

Definition II: *MSNE of the best response game is the set of probabilities $\vec{\mu} = (\mu_1, \mu_2...)$ and $\vec{\eta} = (\eta_1, \eta_2...)$ one for EU and one for OU such that the players get the same payoff (utility gain) when they play a strategy with probability μ_i and η_i respectively.*

The probabilities for EU to choose L_1 and L_2 are denoted as μ_1 and μ_2, respectively. Additionally, the probabilities for OU to choose Y_1 and Y_2 are denoted as η_1 and η_2. As per

Definition II, OU is required to receive the same utility for both prices Y_1 and Y_2, irrespective of EU's mixing strategy, while EU should obtain the same utility for playing L_1 and L_2, regardless of OU's mixing strategy. Therefore, we can express this as follows:

$$13 * \mu_1 + 10 * \mu_2 = 12 * \mu_1 + 11 * \mu_2 \tag{6.9}$$

$$13 * \eta_1 + 15 * \eta_2 = 14 * \eta_1 + 11 * \eta_2 \tag{6.10}$$

Algorithm 4 Orthogonality Centric Pricing: Solution

1. **Setup:**
   - 1.1. Initialize the known parameters in the utility definitions.
   - 1.2. The step size for the simulation is set at 500.
   - 1.3. The optimal price range of the base station is divided into 500 intervals between y_{min} and y_{max}, and is given by u. Similarly, the data length range between l_{min} and l_{max} is divided into 500 segments and is denoted by v.
2. **Computations:**
   - A utility matrix of size 500x500 is created with the prices as rows and data lengths as columns
   - **For:** all rows in the table
     - choose v: one data length that yields the highest utility for the user using Equation (6.8)
   - **For:** all columns in the table
     - choose v: one price that yields the highest utility for the base station using Equation (6.3)
   - **For:** all rows in the table
     - **For:** all columns in the table
       - Iterate over all cells to eliminate entries that both the user and base station would never play (IESDS)
       - Mark all the mutual best responses
     - **If:** No mutual responses are found - Pure Strategy Nash Equilibrium solution does not exist
       - Initialize a probability vector corresponding to the size of the reduced matrix
       - Formulate and solve the set of quadratic equations for obtain the mixing probabilities for the MSNE solution.
3. **Results:** The optimal $\{y^*_{\text{noma}}, l^*_j\}$ is declared as the game solution and the corresponding utilities for the user U_{user} and base station U_{BS} are computed.

As the probabilities satisfy the condition $\sum \mu_i = \sum \eta_j = 1$, there are four equations and four unknowns that can be solved to determine the mixing probabilities that result in a

MSNE solution. For the given example, the mixing probabilities for EU are determined to be $\mu_1 = 0.5, \mu_2 = 0.5$ and for OU are $\eta_1 = 4/5, \eta_2 = 1/5$, which constitute the MSNE solution for the game.

To establish the mutual best response for the NOMA data shifting problem, a computational approach was employed as per the instructions outlined as Algorithm 4. This algorithm is a useful reference for executing multimedia applications and can be fine-tuned by adjusting the system parameters represented by $a1$ through $a4$. During periods of low multimedia activity, the two-dimensional searching table can be apprised with new values. Alternatively, to lessen the computation complexity and minimize the latency between data transmissions, the mutual best response can be directly determined by probing the table whenever the game needs to be played.

6.5 Numerical Analysis

In this section, the efficiency of the projected profit-driven data shifting protocol was assessed using multimedia data encoded with the MPEG-4 H.265 codec. The video sequences used in the simulation are the standard $Foreman$ video and $NetflixPier - Seaside$ video, encoded in Group of Pictures (GOP) format. The independent data set is encoded with only I frames, whereas the forward-dependent set is encoded with both I and P frames. The inter-dependent data set is obtained by encoding the GOP with I, P, and B frames.

From these data sets, the values of q_j and l_j are derived. The bit error rate (BER) is set at 1e-6, and the user personal preference γ is set to 0.5. The cost parameters C_{oma} and C_{noma} are set to 1 and 0.2, respectively.

The break-even point between NOMA and OMA resource blocks occurs when the base station serves 5 users in a NOMA block. If the block is utilized by more than 5 users, the base station can earn more income in a NOMA resource block. In the simulation, a total of

8 users are assisted in the NOMA resource block, with 4 users bringing interference to the data of other users.

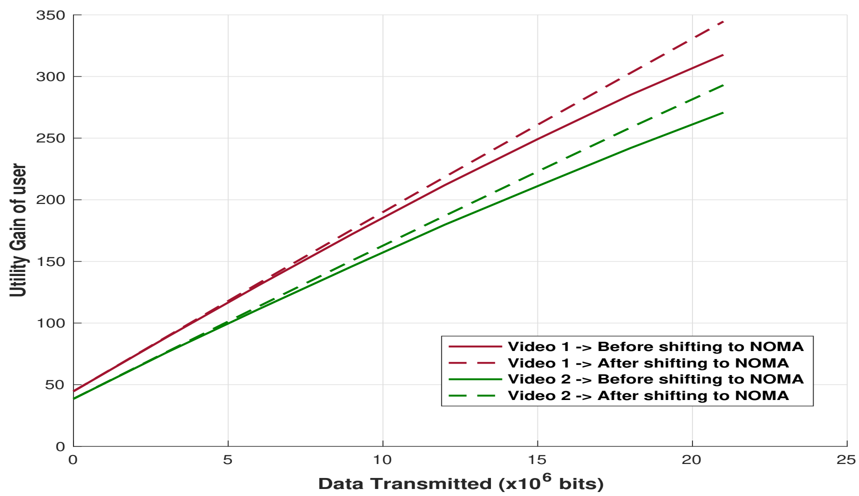

Figure 6.4: Analysis of user's utility gain

Two different video sequences were used to determine the user's utility gain using Equation (6.8), and the results were plotted in Figure 6.4 [9]. The bold lines in the graph denote the overall utility achieved without using the proposed pricing approach. Here all I-frames were conveyed using the OMA link and the remaining frames were conveyed using the NOMA link. The dashed lines in the graph signify the utility achieved using the proposed game solution to determine the split between the OMA and NOMA links. The total number of bits transmitted through the NOMA link was derived using the mutual best response game, with all P and B frames, as well as a portion of I frames, contributing to the game solution y^*_{noma}. The residual I frames were transmitted through the OMA link. The results also imply that the user by shifting some of the content to the NOMA link is able to achieve a higher utility.

Figure 6.5 [9] shows the rise in utility of the base station, calculated using Equation (6.3), for the two simulated videos, namely $Foreman$ and $NetflixPierSeaside$. It is obvious from the graph that the proposed data-shifting scheme results in higher utility for the base station. This is because more users can be assisted by the base station when they move their data to the NOMA resource blocks, which have a lower operating cost C_{noma} compared to the OMA blocks. Consequently, the base station can earn more income by applying the NOMA resource blocks efficiently, leading to greater utility.

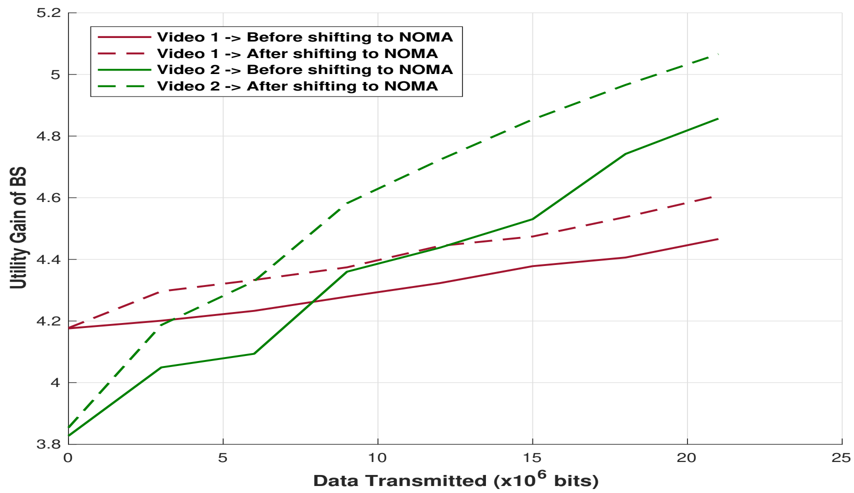

Figure 6.5: Analysis of base station's utility gain

The Figure 6.6 portrays the relationship between the utility gains of the consumer and the base station and the bit error rate of the wireless channel. The utility of both parties drops with the increase in the error rate, as shown in Figure 6.6 (left) and Figure 6.6 (right). The results confirmed that the base station achieves the highest gain when the user swings all the data from OMA to NOMA, signifying its preference for NOMA link due to its benefits such as improved spectral efficiency, higher cell-edge throughput, relaxed channel feedback, and low transmission latency. Still, the user does not achieve the highest utility by moving all the data to NOMA. From Figure 6.6 (left), it can be seen that the consumer benefits prominently from obtaining the service in a OMA+NOMA hybrid network.

The utility of the end user under a fixed budget was assessed using the proposed scheme. The importance-ordered frames were presumed, and a NOMA link was devised to allow concurrent transmission for four users. As shown in Figure 6.7 [8], the user's utility surges with the amount of data conveyed. The simulation results show that a hybrid of OMA and NOMA channels leads to the highest utility for the user. Moreover, the figure on the right

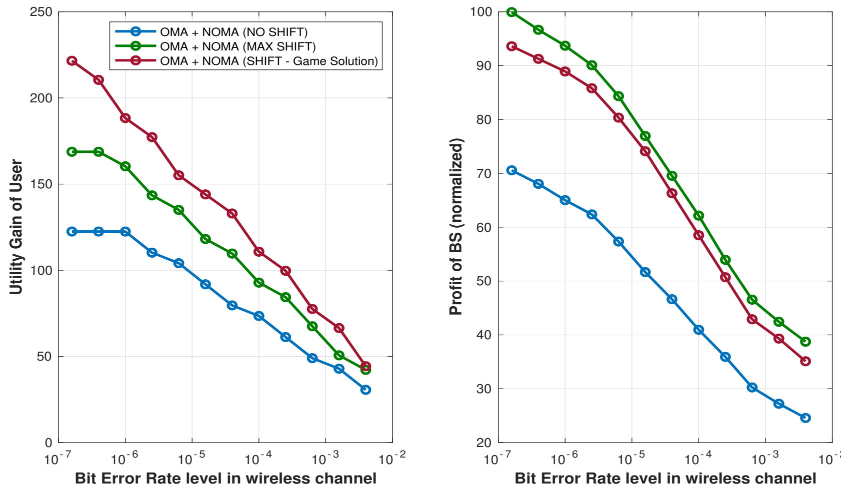

Figure 6.6: Effect of bit error rate on utility gains

elucidates the power transmitted for a single user in an OMA link and a set of n users in a NOMA link. It is obvious that the mobile end consumer can achieve higher utilities for similar power levels by tactically splitting up the data between the NOMA and OMA links via MSNE solution.

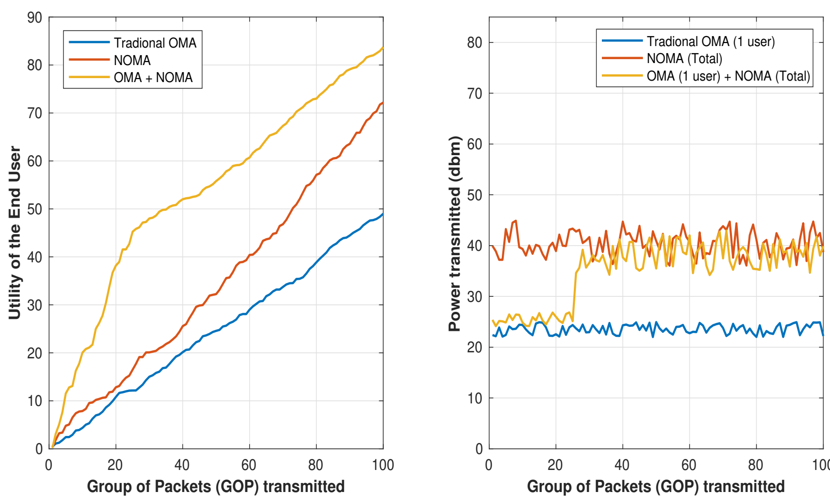

Figure 6.7: Comparison of NOMA, NOMA+OMA and traditional OMA network

The utility of the base station relative to its operating costs denoted by the parameters α and β was evaluated. These parameters were switched between 0 and 1, and the effect of the proposed framework on the base station's utility was analyzed. In the simulation, two

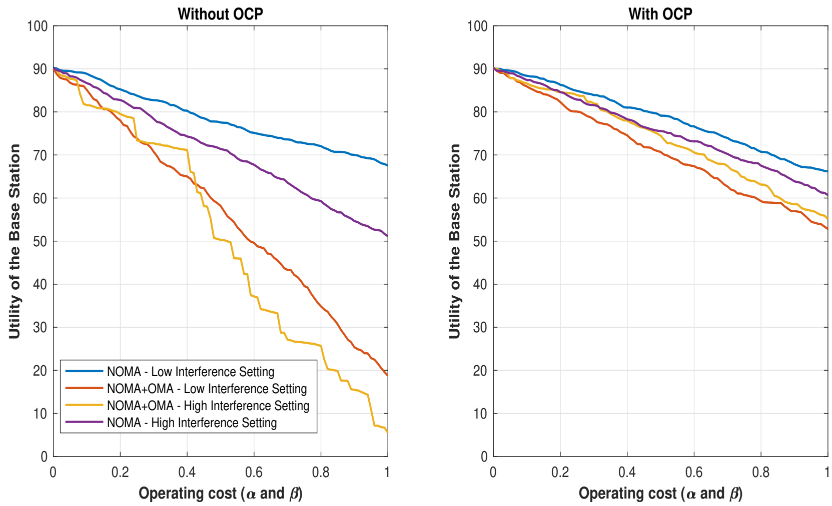

Figure 6.8: Illustration of utilities with proposed pricing scheme

NOMA links were used - one with low interference and one with high interference. The suggested scheme drastically increases the base station's utility than the traditional uniform pricing scheme and this is depicted in Figure 6.8 [8]. Not including the proposed framework, decreases the base station's utility with channel quality and user preference for channels with less interference. Yet, by vigorously allotting rates for resource block usage, the base station is able to evenly dispense the traffic among all available links and lead to consistent revenue irrespective of the resource blocks type used by mobile customers.

6.6 Concluding remarks

Hybrid multiple access network that combines OMA and NOMA options are predicted to take over the future wireless communication technologies. But the main obstacle in hybrid networks that remains, is how to allot user data between the NOMA and OMA blocks. In this chapter, an incentive-driven data-shifting scheme to promote NOMA communications is introduced to address this issue. Utility functions for both the base station and the user were described and their interaction was modeled as a best-response game. Then a solution to the game was obtained and simulations were run to evaluate the effectiveness of the proposed scheme. The simulation results reveal that both the base station and the NOMA wireless user can attain preferable utilities through our suggested incentive technique.

Chapter 7

Conclusion and Future Work

7.1 Conclusions

Proliferation of mobile and Internet ready devices coupled with on-demand multimedia and interactive video services such as video surveillance, entertainment in smart transportation, and online gaming have made wireless communication as one of the rapidly growing technologies. Modern day content-rich applications often requires high processing power, storage, bandwidth, and better resource scheduling.

NOMA has been the advocated resource scheduling technique for 6G wireless communications and beyond. In this dissertation, the Quality of Experience (QoE) issue in NOMA is addressed by leveraging the concept of pricing data quality rather than binary data itself. In **chapter 3**, NOMA Pricing model has been introduced and the results show that the users can achieve higher QoE and the service providers attain better profits.

In **chapter 4**, human psychological effects were taken into consideration of QoE by modeling. Value function and weighting function from Prospect theory are used to achieve even better QoE gain for the mobile customers. NOMA Pricing model was also adapted for device to device communication enabled network in **chapter 5** and hybrid network with support for Orthogonal multiple access and NOMA in **chapter 6**.

The key contribution of this dissertation is to show that user experience based pricing models - similar to airline seating and Uber ride-sharing services has a tremendous potential in wireless networking. In particular, this dissertation shows that users can sense more value for the money spent in a QoE pricing enabled NOMA wireless network.

7.2 Future work

In addition to the contributions discussed, this chapter also provides insights on couple of interesting ideas that are been investigated at the time of writing this dissertation. Some of the open directions for future study are also suggested.

7.2.1 NOMA Coin: Blockchain based token to validate and store transactions in NOMA network

Users in a NOMA network who have a strong channel gain can decode and store signals from weaker users. This cached data can then be transmitted to the intended recipients for a small fee. In **chapter 5**, second price VCG auction was used to provide incentive and promote device to device communication. However, there are several challenges associated with monitoring peer-to-peer monetary transactions in a NOMA network where re-transmission is incentivized. Using the ACH bank transfer system to make payments can also be time-consuming.

These issues can be mitigated by carrying out the transactions on a block chain. This will offer increased privacy and transaction speed. To implement this solution, new crypto currency called NOMAToken that operates on the Ethereum block-chain is proposed. The token is designed to compensate caching relay users and reward validating users.

NOMAToken is a token deployed over the Ethereum blockchain. The sole purpose of the token is to provide a means of payment for transactions in a NOMA network. Blockchains use consensus mechanisms such as Proof-of-Work (PoW), Proof-of-Stake (PoS), Proof-of-Authority (PoA), Practical Byzantine fault-tolerant (PBFT), and Proof-of-Reputation (PoR) [74] to maintain trust between untrusted nodes in a block-chain and mint new tokens in the network. As a part of this work, a new consensus model called Proof-of-QoE (PoQ) has been proposed. PoQ model is tailor made for wireless networks and oversees the overall user satisfaction in the NOMA network. The minting of new NOMATokens are also facilitated through the PoQ consensus model.

7.2.2 IRS assisted NOMA

In NOMA, the signals are overlapping and so the users experience interference. The interference is handled by the receiver device using successive interference cancellation. The interference increases as the distance between user devices decrease. This result in creation of a NOMA non-friendly environment. This results in low fairness rate.

One potential solution for enhancing network coverage in upcoming wireless networks is through the use of an intelligent reflecting surface (IRS) [75]. An IRS consists of numerous passive mirrors/surfaces, and every surface can reflect incoming signals independently by altering the reflection coefficients such as amplitude and phase shift. This allows for an increase in received signal power at the receiver. Recently IRS assisted NOMA communication has been recently studied in the literature [76]. Currently, we are investigating methodology to identify the optimal placement of IRS to improve the network fairness.

7.2.3 Open directions for future study

The focus of this dissertation has been to propose theoretical models to address QoE issues and provide mathematical proof for their correctness. The simulations carried out were using data generated in a laboratory setting. The theories can be tested and further improved using real-life data from a mobile network. Furthermore, H.265 multimedia encoding was used to generate the multimedia data used in this dissertation. The theories can be tested using novel multimedia schemes such as AV1 and VP9.

Prospect theory has proven to mathematically capture the human decision making behavior under non-favorable conditions. In this dissertation, we exploit the fundamentals of the theory to model the utility equations for NOMA network. This can be extended across various disciplines in wireless communication. For example, problems in mobile networks such as spectrum sharing, edge computing, content delivery through cloud and fog networks can be modeled using PT.

Bibliography

[1] K. M. K. Ramamoorthy and W. Wang, "A prospect-theoretic approach for qoe-aware resource allocation in multimedia internet of things," *IEEE Internet of Things Journal*, (under 2nd round of review).

[2] K. M. K. Ramamoorthy and W. Wang, "Qoe-sensitive economic pricing model for wireless multimedia communications using stackelberg game," in *2019 IEEE Global Communications Conference (GLOBECOM)*, pp. 1–6, IEEE, 2019.

[3] K. M. K. Ramamoorthy, W. Wang, and K. Sohraby, "Nomap: A pricing scheme for noma resource block selection and power allocation in wireless communications," in *2021 IEEE International Symposium on Local and Metropolitan Area Networks (LANMAN)*, pp. 1–6, IEEE, 2021.

[4] K. M. K. Ramamoorthy, W. Wang, and K. Sohraby, "Noma resource block as a commodity box: Content-centric qoe-price interplay in wireless multimedia communications," in *2022 IEEE Wireless Communications and Networking Conference (WCNC)*, pp. 2673–2678, IEEE, 2022.

[5] K. M. K. Ramamoorthy and W. Wang, "Human cognition aware qoe for noma pricing: A prospect-theoretic augmentation to non-orthogonal wireless multiple access," in *2022 Intermountain Engineering, Technology and Computing (IETC)*, pp. 1–5, IEEE, 2022.

[6] K. M. K. Ramamoorthy and W. Wang, "Prospect theoretic pricing for qoe modeling in wireless multimedia networking," in *2020 Intermountain Engineering, Technology and Computing (IETC)*, pp. 1–6, IEEE, 2020.

[7] K. M. K. Ramamoorthy, W. Wang, and K. Sohraby, "A power auction approach for non-orthogonal multiple access wireless relay communications," in *ICC 2022-IEEE International Conference on Communications Workshop on Green and Sustainable Networking (GreenNet)*, IEEE, 2023.

[8] K. M. K. Ramamoorthy, W. Wang, and K. Sohraby, "Orthogonality-centric pricing for wireless multimedia multiple access networks," in *ICC 2022-IEEE International Conference on Communications*, pp. 2513–2518, IEEE, 2022.

[9] K. M. K. Ramamoorthy, W. Wang, and K. Sohraby, "Incentivize non-orthogonal multiple access in wireless multimedia communications," in *2023 IEEE Wireless Communications and Networking Conference (WCNC)Workshop on Next Generation Multiple Access for Future Wireless Communications*, IEEE, 2023.

[10] Y. Liu, Z. Qin, M. Elkashlan, Z. Ding, A. Nallanathan, and L. Hanzo, "Nonorthogonal multiple access for 5g and beyond," *Proceedings of the IEEE*, vol. 105, no. 12, pp. 2347–2381, 2017.

[11] Ramneek, P. Hosein, and S. Pack, "User remuneration under congestion: A dynamic and fair pricing strategy for wireless networks," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 7, pp. 7294–7299, 2021.

[12] A. Chakraborty, S. Misra, and A. Mondal, "Qos-aware dynamic cost management scheme for sensors-as-a-service," *IEEE Transactions on Services Computing*, vol. 15, no. 3, pp. 1720–1731, 2022.

[13] N. Zabetian and B. H. Khalaj, "Qoe-aware network pricing, power allocation, and admission control," *IEEE Transactions on Mobile Computing*, pp. 1–10, 2023.

[14] Ramneek, P. Hosein, and S. Pack, "Pricing esim services: Ecosystem, challenges, and opportunities," *IEEE Communications Magazine*, pp. 1–7, 2023.

[15] J. Chen, J. Farooq, and Q. Zhu, "Qos based contract design for profit maximization in iot-enabled data markets," *IEEE Internet of Things Journal*, pp. 1–1, 2023.

[16] D. Kahneman and A. Tversky, "Prospect theory: An analysis of decision under risk," *Econometrica*, vol. 47, no. 2, pp. 263–291, 1979.

[17] V. N. I. Cisco, "Cisco visual networking index: forecast and methodology 2016–2021," *CISCO White paper*, 2017.

[18] A. Khan, L. Sun, and E. Ifeachor, "Qoe prediction model and its application in video quality adaptation over umts networks," *IEEE Transactions on Multimedia*, vol. 14, no. 2, pp. 431–442, 2011.

[19] J. Xu, B. Zhou, C. Zhang, N. Ke, W. Jin, and S. Hao, "The impact of bitrate and gop pattern on the video quality of h. 265/hevc compression standard," in *2018 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC)*, pp. 1–5, IEEE, 2018.

[20] Q. Wang, W. Wang, S. Jin, H. Zhu, and N. T. Zhang, "Smart media pricing (smp): Non-uniform packet pricing game for wireless multimedia communications," in *2016 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, pp. 27–32, IEEE, 2016.

[21] W. Wang and Q. Wang, "Price the qoe, not the data: Smp-economic resource allocation

in wireless multimedia internet of things," *IEEE Communications Magazine*, vol. 56, no. 9, pp. 74–79, 2018.

[22] M. Falkner, M. Devetsikiotis, and I. Lambadaris, "An overview of pricing concepts for broadband ip networks," *IEEE Communications Surveys & Tutorials*, vol. 3, no. 2, pp. 2–13, 2000.

[23] S. He and W. Wang, "Context-aware qoe-price equilibrium for wireless multimedia relay communications using stackelberg game," in *2017 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, pp. 506–511, IEEE, 2017.

[24] S. He and W. Wang, "A generalized best-response smart media pricing economic model for wireless multimedia communications," in *2019 16th IEEE Annual Consumer Communications & Networking Conference (CCNC)*, pp. 1–6, IEEE, 2019.

[25] Z. Su, Q. Xu, M. Fei, and M. Dong, "Game theoretic resource allocation in media cloud with mobile social users," *IEEE Transactions on Multimedia*, vol. 18, no. 8, pp. 1650–1660, 2016.

[26] M. J. Osborne, *Introduction to Game Theory: International Edition*. No. 9780195322484 in OUP Catalogue, Oxford University Press, 2009.

[27] K. M. K. Ramamoorthy, W. Wang, and K. Sohraby, "Stackelberg game-theoretic spectrum allocation for qoe-centric wireless multimedia communications," in *Edge Computing–EDGE 2019: Third International Conference, Held as Part of the Services Conference Federation, SCF 2019, San Diego, CA, USA, June 25–30, 2019, Proceedings 3*, pp. 46–58, Springer, 2019.

[28] K. Yamagishi and T. Hayashi, "Parametric packet-layer model for monitoring video quality of iptv services," in *2008 IEEE International Conference on Communications*, pp. 110–114, IEEE, 2008.

[29] G. Liu, Z. Wang, J. Hu, Z. Ding, and P. Fan, "Cooperative noma broadcasting/multicasting for low-latency and high-reliability 5g cellular v2x communications," *IEEE Internet of Things Journal*, vol. 6, no. 5, pp. 7828–7838, 2019.

[30] A. Maatouk, M. Assaad, and A. Ephremides, "Minimizing the age of information: Noma or oma?," in *IEEE INFOCOM 2019-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, pp. 102–108, IEEE, 2019.

[31] D. Duchemin, J.-M. Gorce, and C. Goursaud, "Code domain non orthogonal multiple access versus aloha: A simulation based study," in *2018 25th International Conference on Telecommunications (ICT)*, pp. 445–450, IEEE, 2018.

[32] K. M. K. Ramamoorthy and W. Wang, "Profit-driven cache delegation: A game-theoretic wireless multimedia offloading solution," in *ICC 2021-IEEE International*

Conference on Communications, pp. 1–6, IEEE, 2021.

[33] Z. Na, Y. Liu, J. Shi, C. Liu, and Z. Gao, "Uav-supported clustered noma for 6g-enabled internet of things: Trajectory planning and resource allocation," *IEEE Internet of Things Journal*, vol. 8, no. 20, pp. 15041–15048, 2020.

[34] X. Liu, H. Ding, and S. Hu, "Uplink resource allocation for noma-based hybrid spectrum access in 6g-enabled cognitive internet of things," *IEEE Internet of Things Journal*, vol. 8, no. 20, pp. 15049–15058, 2020.

[35] C. Liang, F. R. Yu, H. Yao, and Z. Han, "Virtual resource allocation in information-centric wireless networks with virtualization," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 12, pp. 9902–9914, 2016.

[36] J. Choi, "Effective capacity of noma and a suboptimal power control policy with delay qos," *IEEE Transactions on Communications*, vol. 65, no. 4, pp. 1849–1858, 2017.

[37] B. Di, L. Song, Y. Li, and G. Y. Li, "Non-orthogonal multiple access for high-reliable and low-latency v2x communications in 5g systems," *IEEE journal on selected areas in communications*, vol. 35, no. 10, pp. 2383–2397, 2017.

[38] L. Wei, Y. Chen, D. Zheng, and B. Jiao, "Secure performance analysis and optimization for fd-noma vehicular communications," *China Communications*, vol. 17, no. 11, pp. 29–41, 2020.

[39] Q.-T. Vien, T. A. Le, C. V. Phan, and M. O. Agyeman, "An energy-efficient noma for small cells in heterogeneous cran under qos constraints," in *European Wireless 2017; 23th European Wireless Conference*, pp. 1–6, VDE, 2017.

[40] W. Hao, M. Zeng, Z. Chu, and S. Yang, "Energy-efficient power allocation in millimeter wave massive mimo with non-orthogonal multiple access," *IEEE Wireless Communications Letters*, vol. 6, no. 6, pp. 782–785, 2017.

[41] M. J. Osborne *et al.*, *An introduction to game theory*, vol. 3. Oxford university press New York, 2004.

[42] A. Tversky and D. Kahneman, "Advances in prospect theory: Cumulative representation of uncertainty," *Journal of Risk and uncertainty*, vol. 5, pp. 297–323, 1992.

[43] L. Xie, Z. Su, N. Chen, Q. Xu, Y. Fan, and A. Benslimane, "A game theory based scheme for secure and cooperative uav communication," in *ICC 2021-IEEE International Conference on Communications*, pp. 1–6, IEEE, 2021.

[44] T. Li and N. B. Mandayam, "When users interfere with protocols: Prospect theory in wireless networks using random access and data pricing as an example," *IEEE Transactions on Wireless Communications*, vol. 13, no. 4, pp. 1888–1907, 2014.

[45] D. D. Clark, J. Wroclawski, K. R. Sollins, and R. Braden, "Tussle in cyberspace: defining tomorrow's internet," *IEEE/ACM transactions on networking*, vol. 13, no. 3, pp. 462–475, 2005.

[46] J. Du, W. Cheng, G. Lu, H. Cao, X. Chu, Z. Zhang, and J. Wang, "Resource pricing and allocation in mec enabled blockchain systems: An a3c deep reinforcement learning approach," *IEEE Transactions on Network Science and Engineering*, vol. 9, no. 1, pp. 33–44, 2021.

[47] C.-H. Lee, "Prospect theoretic user satisfaction in wireless communications networks," in *2015 24th Wireless and Optical Communication Conference (WOCC)*, pp. 195–200, IEEE, 2015.

[48] D. Prelec, "The probability weighting function," *Econometrica*, pp. 497–527, 1998.

[49] K. Higuchi and A. Benjebbour, "Non-orthogonal multiple access (noma) with successive interference cancellation for future radio access," *IEICE Transactions on Communications*, vol. 98, no. 3, pp. 403–414, 2015.

[50] A. Asadi, Q. Wang, and V. Mancuso, "A survey on device-to-device communication in cellular networks," *IEEE Communications Surveys & Tutorials*, vol. 16, no. 4, pp. 1801–1819, 2014.

[51] S. He, W. Wang, and K. Sohraby, "Qoe-centric multimedia relay in energy efficient noma wireless communications," in *ICC 2019-2019 IEEE International Conference on Communications (ICC)*, pp. 1–6, IEEE, 2019.

[52] Y. B. Song, H. S. Kang, and D. K. Kim, "5g cellular systems with d2d assisted noma relay," in *2016 URSI Asia-Pacific Radio Science Conference (URSI AP-RASC)*, pp. 1–3, IEEE, 2016.

[53] Y. Dai, M. Sheng, J. Liu, N. Cheng, X. Shen, and Q. Yang, "Joint mode selection and resource allocation for d2d-enabled noma cellular networks," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 7, pp. 6721–6733, 2019.

[54] A. Khokar, R. Bajpai, and N. Gupta, "Best user selection for noma-aided full-duplex cooperative d2d communication system," in *2020 27th International Conference on Telecommunications (ICT)*, pp. 1–5, IEEE, 2020.

[55] N. R. Suri and Y. Narahari, "An auction algorithm for procuring wireless channel in a heterogenous wireless network," in *2006 IFIP International Conference on Wireless and Optical Communications Networks*, pp. 5–pp, IEEE, 2006.

[56] S. Althunibat, A. Abu-Al-Aish, W. F. A. Shehab, and W. H. Alsawalmeh, "Auction-based data gathering scheme for wireless sensor networks," *IEEE Communications Letters*, vol. 20, no. 6, pp. 1223–1226, 2016.

[57] T. Han, T. Xing, N. Zhang, K. Liu, B. Tang, and Y. Liu, "Wireless spectrum sharing via waiting-line auction," in *2008 11th IEEE Singapore International Conference on Communication Systems*, pp. 1031–1035, IEEE, 2008.

[58] C. Xu, L. Song, D. Zhu, and M. Lei, "Subcarrier and power optimization for device-to-device underlay communication using auction games," in *2014 IEEE International Conference on Communications (ICC)*, pp. 5526–5531, IEEE, 2014.

[59] D. Ho, G. S. Park, and H. Song, "Auction-based resource negotiation for flexible video traffic offloading over wireless networks," in *2017 International Conference on Computing, Networking and Communications (ICNC)*, pp. 6–12, IEEE, 2017.

[60] V. Krishna, *Auction Theory*. Elsevier, 1 ed., 2002.

[61] K. Leyton-Brown and Y. Shoham, "Essentials of game theory: A concise multidisciplinary introduction," *Synthesis lectures on artificial intelligence and machine learning*, vol. 2, no. 1, pp. 1–88, 2008.

[62] M. Tang, H. Pang, S. Wang, L. Gao, J. Huang, and L. Sun, "Multi-dimensional auction mechanisms for crowdsourced mobile video streaming," *IEEE/ACM Transactions on Networking*, vol. 26, no. 5, pp. 2062–2075, 2018.

[63] M. Jackson, "Matching, auctions, and market design," *SSRN Electronic Journal*, 04 2013.

[64] M. Elbayoumi, W. Hamouda, and A. Youssef, "A hybrid noma/oma scheme for mtc in ultra-dense networks," in *GLOBECOM 2020-2020 IEEE Global Communications Conference*, pp. 1–6, IEEE, 2020.

[65] L. Dai, B. Wang, Z. Ding, Z. Wang, S. Chen, and L. Hanzo, "A survey of non-orthogonal multiple access for 5g," *IEEE communications surveys & tutorials*, vol. 20, no. 3, pp. 2294–2323, 2018.

[66] M. A. Hoque, B. Finley, A. Rao, A. Kumar, P. Hui, M. Ammar, and S. Tarkoma, "Context-driven encrypted multimedia traffic classification on mobile devices," *Pervasive and Mobile Computing*, vol. 88, p. 101737, 2022.

[67] P. Xu, J. Quan, Z. Yang, G. Chen, and Z. Ding, "Performance analysis of buffer-aided hybrid noma/oma in cooperative uplink system," *IEEE Access*, vol. 7, pp. 168759–168773, 2019.

[68] L. Liu, B. Sun, Y. Wu, and D. H. Tsang, "Latency optimization for computation offloading with hybrid noma–oma transmission," *IEEE Internet of Things Journal*, vol. 8, no. 8, pp. 6677–6691, 2021.

[69] N. Nomikos, T. Charalambous, D. Vouyioukas, G. K. Karagiannidis, and R. Wichman, "Hybrid noma/oma with buffer-aided relay selection in cooperative networks," *IEEE*

Journal of Selected Topics in Signal Processing, vol. 13, no. 3, pp. 524–537, 2019.

[70] M.-J. Sheng, C. Joe-Wong, S. Ha, F. M. F. Wong, and S. Sen, "Smart data pricing: Lessons from trial planning," in *2013 Proceedings IEEE INFOCOM*, pp. 3327–3332, IEEE, 2013.

[71] Z. Wang, Z. Zhang, S. Qing, Y. Xu, X. Wan, and Z. Fan, "Price-based resource allocation in noma system with hardware impairments," in *2021 IEEE/CIC International Conference on Communications in China (ICCC)*, pp. 973–977, 2021.

[72] X. Wen, H. Zhang, H. Zhang, and F. Fang, "Interference pricing resource allocation and user-subchannel matching for noma hierarchy fog networks," *IEEE Journal of Selected Topics in Signal Processing*, vol. 13, no. 3, pp. 467–479, 2019.

[73] S. S. Abidrabbu and H. Arslan, "Efficient power allocation for cognitive radio noma using game-theoretic based pricing strategy," in *2021 IEEE 93rd Vehicular Technology Conference (VTC2021-Spring)*, pp. 1–5, 2021.

[74] H. N. Abishu, A. M. Seid, Y. H. Yacob, T. Ayall, G. Sun, and G. Liu, "Consensus mechanism for blockchain-enabled vehicle-to-vehicle energy trading in the internet of electric vehicles," *IEEE Transactions on Vehicular Technology*, vol. 71, no. 1, pp. 946–960, 2022.

[75] Q. Wu and R. Zhang, "Intelligent reflecting surface enhanced wireless network: Joint active and passive beamforming design," in *2018 IEEE Global Communications Conference (GLOBECOM)*, pp. 1–6, IEEE, 2018.

[76] A. Ihsan, W. Chen, M. Asif, W. U. Khan, Q. Wu, and J. Li, "Energy-efficient irs-aided noma beamforming for 6g wireless communications," *IEEE Transactions on Green Communications and Networking*, vol. 6, no. 4, pp. 1945–1956, 2022.