PSYCHOPHYSICS TESTBED AND EXPERIMENTS FOR ASSESSING END-USER PERCEPTION OF VIDEO QUALITY OF SERVICE (QoS) OVER WIRELESS CHANNELS

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A thesis submitted to the

Graduate School—New Brunswick

Rutgers, The State University of New Jersey

in partial fulfillment of the requirements

for the degree of

Master of Science

Graduate Program in Electrical and Computer Engineering

Written under the direction of

Professor Narayan B. Mandayam

and approved by

New Brunswick, New Jersey

May, 2016

ABSTRACT OF THE THESIS

Psychophysics Testbed and Experiments for Assessing End-user Perception of Video Quality of Service (QoS) over Wireless Channels

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As part of radio resource management (RRM), pricing mechanisms that influence wireless device behavior and thereby drive systems to better operating points have been addressed amply in the RRM literature. These mechanisms essentially are borne out of Expected Utility Theory (EUT) based microeconomics approaches, and implemented via engineered system design, i.e., embedding these strategies in the link layer and network layer protocols that are executed by wireless devices. When a wireless service provider controls access to end-users via differentiated and hierarchical monetary pricing, then the performance of the network is directly subject to end-user decision-making that has shown to deviate from EUT. In this thesis, Prospect Theory (PT), a Nobel prize winning theory that explains real-life decision-making and its deviations from EUT behavior, is used to illuminate the end-user behavior from a cognitive psychology perspective in such a wireless network. Specifically, we conduct psychophysics

experiments, to analyze how end-users evaluate the video QoS (quality of service) over wireless channels. A key aspect of PT modeling is that end-users evaluate objective probabilities with a subjective bias, often captured by a probability weighting function. Based on our human subject studies, we numerically estimate parameters for the popularly used Prelec's probability weighing function, thereby showing how end-users evaluate uncertainty in wireless QoS. The findings here provide useful pointers for designing optimal pricing and resource management algorithms in wireless networks as well as understanding the interplay between the price offerings, resource allocation by the service providers (SP) and the service choices made by end-users.

Acknowledgements

I would first like to express my sincere gratitude to my thesis adviser Dr. Narayan Mandayam, a Professor with the Wireless Information Network Laboratory (WINLAB) at Electrical and Computer Engineering Department. He consistently allowed this thesis to be my own work, but steered me into the right direction whenever he thought I needed it. I sincerely appreciate his patient guidance and encouragement.

I would also like to acknowledge the engineers of WINLAB who were involved in building the testbed platform for this research project: Ivan Seskar and Nilanjan Paul. Without their passionate participation and know-how, the testbed platform could not be successfully built.

I would also like to thank Dr. Arnold Glass, a Professor with Psychology Department. Without his expertise in Cognitive Psychology, this human subject studies could not be successfully conducted. Additionally, I would like to thank undergraduate students from Psychology Department who assisted psychophysics experiment data collection: Alysia Tsui, Jiayu Lu, Zihuan Cao and Christopher Metry.

Also, I would like to acknowledge Dr. Roy Yates and Dr. Zoran Gajic, Professors of the Electrical and Computer Engineering as the committee members of my thesis defense. I am gratefully indebted to their valuable comments on this thesis.

Lastly but not least, I must express my very profound gratitude to my parents and sister for their endless support and love through my whole life including the process of researching and writing this thesis. No matter what things happened, they always encouraged me to live strongly and face the difficulties positively. Also I want to thank my beloved soul mate, Emma, and all of my friends for continuous encouragement throughout my years of study. This accomplishment would not have been possible without them. Thank you.

This work is supported by a U.S. National Science Foundation (NSF) Grant (No. 1421961) under the NeTS program.

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Chapter 1

Introduction

1.1 Motivation

As the cell phone has become the smart phone and thousands of "apps" (both trivial and profound) have emerged, there is an awareness that something important is happening around us. Those of us who have mastered this emerging "smart world"seem to move more easily through its complexities and problems. We know there are traffic jams ahead and that our flights have been canceled, and have already altered our routes to the airport and changed our tickets, while the rest move toward trouble in blissful unawareness. Our dinner reservations have been made, and the movie we will watch has been downloaded. Over time, the rest will eventually master those plentiful "apps," and as they become aware of this new "smart world" they will use it in abundance too. Most "app" of today depend on internet services that are already available they make them easy to access and available in a mobile application. In these smart societies, a broad range of new applications that enhance safety, convenience and productivity will fundamentally require that every person (and their devices) must be directly or indirectly connected to the internet. The result of such applications is an unprecedented demand for wireless data capacity while spectrum and infrastructure necessary to support it are still lagging behind.

Beyond smart phones, of which there are significantly more in developed countries, the number of mobile phones in the world is approaching 7B, even creating a reality that in some parts of the world, there are more people with access to a phone than with access to electricity at home. The advent of machine-to-machine (M2M) communications [1, 2] adds increased pressure on wireless system capacity. The wireless research community and industry at large are actively seeking out solutions that are needed to provide the capacity required to support the exploding volume of future wireless applications and services. In fact, there is a recognition and push in both industry and academia towards the goal of achieving "1000 times" of current capacity for wireless [3–5]. The solution approaches range from spectrally agile cognitive radios with authorized shared access (ASA) spectrum sharing [6, 7], to use of higher frequency spectrum [8, 9] as well as smaller and denser cell deployments [10, 11]. The result has been research and studies on heterogeneous networks (HetNets) [12–14], and self-organizing networks (SONS) [15, 16].

While the design of smaller and denser cells is an area of intense research activity to support the exploding volume of future wireless applications and services, an increasingly necessary requirement of such design is the availability of scalable backhaul solutions. Solutions to such backhaul include point-to-point wireless links using a massive number of multiple antennas and perhaps higher and higher frequency spectrum such as 28 GHz and even 60 GHz. Regardless of the exact details of these technological solutions, providing a spatially high density of wireless/wired backhaul is expensive and the overwhelming demands on wireless capacity fundamentally remain. Moreover, while research and development along the above directions is necessary and important, the reality is that the state-of-the-art systems are nowhere near the "1000 times" capacity target goals and perhaps even an order of magnitude away, with many challenges that need to be overcome [5, 14].

As a complementary approach to the above activity, policing mechanisms (often referred to as “pricing”) that influence wireless device behavior and thereby drive systems to better operating points have been addressed amply in the radio resource management literature (e.g., some of the the earliest examples in the context of power control and medium access are in [17–23]). These mechanisms essentially are borne out of Expected Utility Theory (EUT) [24] based on microeconomics approaches, where the externalities are sought to be internalized or held in check through system level measures. As discussed in the radio resource management literature, the implementation of these pricing mechanisms can be enabled by engineered system design, i.e., embedding these strategies in the link layer and network layer protocols that are executed by wireless systems and devices. These techniques have worked well in wireless systems in the past, but the recent and continued explosion of data demand has prompted wireless service providers (SPs) to control access and services being provided to end-users via differentiated and hierarchical monetary pricing schemes [25, 26]. Associated with such dynamic pricing is also dynamic spectrum access as has been detailed in the rich literature on cognitive radios (e.g. [27–31]).

We believe that it will increasingly become common that end-users may have to make decisions on rate and price offerings that may be presented to them when they need service in dynamic spectrum settings with dense data users. Moreover, the service offers made by the SP will now come with a probabilistic guarantee due to constraints on infrastructure, availability of spectrum and the presence of interference. A report published by the Federal Communications Commission (FCC) which measured the actual rates delivered by the SPs of more reliable wired internet service, shows that advertised rates are not delivered by most of the SPs all the time [32]. Moreover, in an attempt to measure the actual delivered service from wireless SPs as well as to fully inform the users about the actual wireless broadband service they are purchasing, the FCC has recently launched a project in which users can send feedback to the

FCC via a smart phone application, which collects information including the downlink and uplink rates, latency, as well as packet loss of the wireless network [33]. Thus, dynamic pricing with uncertainty in guarantees opens up an entirely new paradigm by exposing the overall design of the wireless network to the decisions of end-users based on their monetary perceptions of the "value" of the service. Decision making in real-life (especially monetary transactions) is often guided by perceptions that deviate from the precepts of EUT [34].

Motivated by these emerging wireless networking scenarios, we turn to Prospect Theory (PT) [35], a Nobel prize winning theory developed by Kahneman and Tversky that explains real-life decision-making and its deviations from EUT behavior. While the main ideas and models behind early PT were developed based on responses/decisions of players involving monetary transactions, the behavioral deviations from EUT are general enough that they have widespread application in many areas [34, 36–38]. Further, preliminary investigation in the context of an exemplary random access and data pricing problem [39] reveals that deviations from EUT under data pricing are harmful to system performance so necessitates application of PT in the design of pricing schemes for wireless systems to manage network loads.

1.2 Research Objective

In this thesis, Prospect Theory (PT), a Nobel prize winning theory that explains real-life decision-making and its deviations from EUT behavior, is used to illuminate the end-user behavior in wireless network from a cognitive psychology perspective. Specifically, we performed psychophysics experiments to analyze how end-users evaluate the video QoS (quality of service) over wireless channels. Subjects' ratings of video QoS were used to construct Prelec's probability weighing function (PWF) [40] for PT. The research conclusions will provide useful pointers to formulate a game theoretic analysis of the interplay between the pricing schemes offered by service providers (SPs) that state service uncertainties and the service choices made by end-users, so that suggest solutions for managing the ever increasing demand for data.

1.3 Organization of the Thesis

The rest of the thesis is organized as follows.

In Chapter 2, related works on data pricing and understanding the end-user's quality of experience (QoE) in wireless networks are introduced.

In Chapter 3, a background of this thesis, Prospect Theory (PT), is introduced. Specifically, probability weighting effect (PWE) and framing effect (FE) are explored.

In Chapter 4, the overall design of the psychophysics experiment is described. It includes full details of the testbed platform and the metrics.

In Chapter 5, the experimental results data analysis are be discussed.

Finally, Chapter 6 concludes the thesis and discusses some remaining issues for the future works.

Chapter 2

Related Works

2.1 Data Pricing

It has been recognized for quite some time that a measurement of user satisfaction must be included in the assessment of the efficiency of the network [41]. Flat-rate pricing adopted by service providers (SPs) and still widely used today due to its simplicity, has been shown to be suboptimal. A wide range of pricing strategies have been proposed, including time-dependent pricing [42], usage-based pricing [43], pricing involving content-provider [44], non-linear pricing [45], tiered pricing [46], and Paris-Metro-Pricing [47]. For wireless networks, optimal pricing strategies for the scenario of bandwidth-sharing between WiFi and WiMAX, and heterogeneous networks has been studied in [48, 49]. Two of the most common approaches towards exploiting the power of pricing are game theory and optimization, each containing a huge body of literature. Contrary to the optimization approach, which often maximizes a utility function with congestion or fairness as a constraint to the problem, game theory captures the processes of utility-maximization of the users and the SPs simultaneously, and has proved to be an effective and reliable method for modeling the interactions between the SP and the user, for describing the competition between multiple SPs, and for characterizing the noncooperative and selfish nature of the users. In [50], authors provided a detailed review of the commonly used models such as the two-person non-zero sum game, the leader-follower game (also known as the Stackelberg game), and the cooperative game, under the scenario with one SP, as well as multiple competing service providers. As mentioned earlier, the notion of pricing of radio resources [17–23] and its use in dynamic spectrum access (DSA) [27–30] is also well known.

2.2 Understanding End-user Quality of Experience (QoE) in Wireless Network

However, despite all the related works mentioned previously, not much attention has been paid to the problem of the increasing influences that the end-user's decision-making is having on the network's performance. This is an important problem since game theory relies heavily on EUT, which cannot effectively predict people's decisions under situations involving risks and uncertainties. Although various attempts have been made to study and model the deviations of the end-user's decision-making from the expectation of the network's designer [51, 52], or to simply better understand the end-users' quality of experience (QoE) [53–56], these are still grounded in Expected Utility Theory (EUT) and fail to fully illuminate end-user behavior. It has also been revealed that mobile Internet users' intention to repurchase the service was significantly related to "experienced value" and "satisfaction" [57]. While these findings highlight the importance of emphasizing user-experience when defining and assessing quality of service (QoS), traditionally, improvement in network service has followed a bottom-up approach, assuming that optimization of performance at the engineering design level will translate directly into an improved user experience. However, research is needed to identify how resource allocation mechanisms impact the "value" of that resource to users and conversely, how end-user behavior impacts resource allocation.

Chapter 3

Background: Prospect Theory (PT)

The main focus of this thesis is to investigate how end-users evaluate the video QoS over wireless channels, specifically by using Prospect Theory (PT) [35] as a tool for analysis. Here, we begin with a brief background of PT as a description of some preliminary work.

The rationality assumption in game theory [58], which states that a player's decision making process is often assumed to be following the axioms and theorems established in Expected Utility Theory (EUT) [24], has long been questioned by behavioral science [59]. Although EUT explains most of the people's decision making successfully, paradoxes have been observed in real life that contradict the predictions of EUT [60]. Alternative theories explaining human's decision making processes were raised in the 1970s, with the most successful one being Prospect Theory.

EUT provides an approach to evaluate a prospect L, i.e., a contract that will yield M different outcomes $o_i, i = 1, \cdots, M$ and each outcome occurs with probability $p_i, \forall i = 1, \cdots, M$ where $\sum_{i=1,\cdots,M} p_i = 1$. EUT determines that people evaluate the prospect as

$$u^{EUT}(L) = \sum_{i=1}^{M} p_i v^{EUT}(o_i), \tag{3.1}$$

i.e., the expected value of all possible outcomes. $v^{EUT}(\cdot)$ is a person's value function of the outcomes and it is often assumed to be concave in EUT. However, PT suggests that the prospect L is evaluated by people as

$$u^{PT}(L) = \sum_{i=1}^{M} w(p_i) v^{PT}(o_i), \tag{3.2}$$

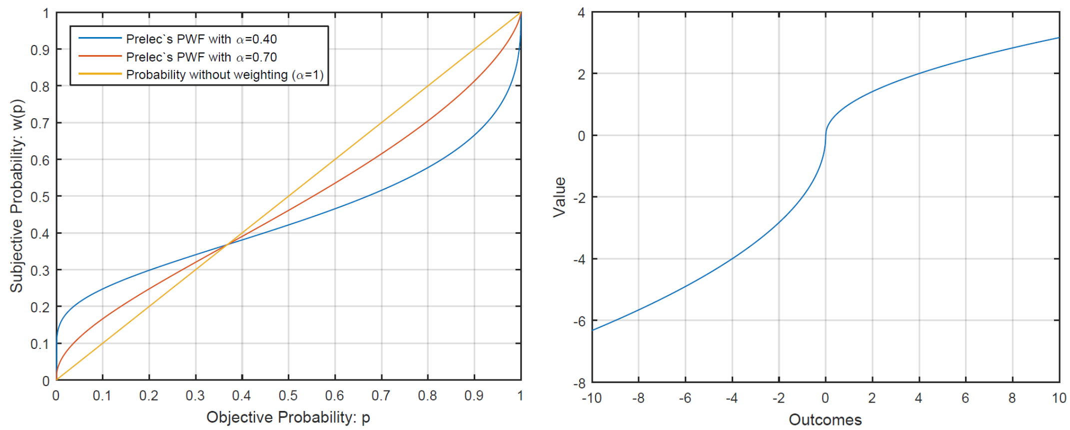
This valuation is significantly different from EUT because of the following two effects: the Probability Weighting Effect (PWE) and the Framing Effect (FE).

3.1 Probability Weighting Effect (PWE)

According to PT, people use their subjective probabilities $w(p_i)$ rather than objective probabilities p_i to weigh the values of possible outcomes. Moreover, people tend to over-weigh low probability outcomes and under-weigh moderate and high probability outcomes. While there have been several efforts to identify appropriate probability weighting functions (PWFs), in the preliminary developments in this thesis, we will use the one identified by Prelec [40] that captures the over-weighting and under-weighting of probabilistic outcomes as follows (Figure 3.1(a)):

$$w(p) = \exp\left\{-(-\ln p)^{\alpha}\right\}, \quad 0 < \alpha \leq 1 \tag{3.3}$$

where $\alpha \in (0, 1]$ is the parameter which reveals how a person's subjective evaluation distorts the objective probability and a smaller α describes a more curved probability weighting function.



(a) Prelec's probability weighting function with three different values of α. The straight line ($\alpha = 1$) is for EUT.

(b) Framing Effect: value function of gains and losses about reference point 0.

Figure 3.1 Prospect Theory: Probability Weighting and Framing Effects

3.2 Framing Effect (FE)

PT [35] states that people determine the value of an outcome by considering the relative gains or losses regarding a reference point. PT also proposes that the value function should be a concave function of gains and a convex function of losses with the convex part usually having a steeper slope (Figure 3.1(b)). In other words, "losses loom larger than gains." However, we do not consider this framing effect (FE) here. Note that the focus of this thesis is on PWE, especially on Prelec's PWF (Equation 3.3, [40]) parameterized by $\alpha \in (0, 1]$.

3.3 Allais' Paradox

These two effects can be illustrated with the famous Allais' Paradox [60]. In [35], the authors provided a variation of the Allais' paradox as shown in the following table that was posed to people. Specifically, there were two problems in the experiment and for each problem, the respondents were asked to choose between either of the two prospects

(A or B). As a result, it was found that the majority (82%) of the participants chose B in problem 1 and the majority (83%) of the participants chose A in problem 2.

	Prospect A	Prospect B
Problem 1	\$2500 with probability 0.33 \$2400 with probability 0.66 \$0 with probability 0.01	\$2400 with certainty
Problem 2	\$2500 with probability 0.33 \$0 with probability 0.67	\$2400 with probability 0.34 \$0 with probability 0.66

According to EUT, the expected utility of each prospect can be calculated with Equation 3.1, where we have used $L \in \{1A, 1B, 2A, 2B\}$ to denote the portfolio of the payoffs and the occurrence probabilities of a set of events $(\vec{v}^{EUT}, \vec{p})$ under a certain alternative, with $\vec{v}^{EUT}$ representing the payoffs of all the potential outcomes, and $\vec{p}$ representing the corresponding probabilities of occurrence. The summation is over all M possible outcomes. Thus, a preference of 1B over 1A implies

$$u^{EUT}(1A) = 0.33 \cdot v^{EUT}(2500) + 0.66 \cdot v^{EUT}(2400) + 0.01 \cdot v^{EUT}(0) \tag{3.4}$$

$$< 1.00 \cdot v^{EUT}(2400) = u^{EUT}(1B), \tag{3.5}$$

which is equivalent to

$$0.33 \cdot v^{EUT}(2500) < 0.34 \cdot v^{EUT}(2400). \tag{3.6}$$

Meanwhile, the choice of 2A over 2B implies

$$u^{EUT}(2A) = 0.33 \cdot v^{EUT}(2500) > 0.34 \cdot v^{EUT}(2400) = u^{EUT}(2B), \tag{3.7}$$

where the two results (3.6 and 3.7) produce a contradiction. This observation illustrates the situation where EUT fails to accurately describe people's real-life decisions. However, PT can successfully explain the decisions the respondents made in the above experiments. In problem 1, since alternative B provides a guaranteed payoff, that payoff becomes the reference point when framing the payoff of each outcome under the other alternative. Thus, \$2500 becomes a gain of \$100, while \$0 becomes a loss of \$2400. It can then be readily seen that if the probability 0.01 is over-weighted as depicted in Figure 3.1(a), then most people would have indeed preferred B to A. The same argument applies to problem 2. By PT, $\alpha = 0.5$ and $v^PT(\cdot)$ is linear, it can be easily shown that

$$u^{PT}(1A) = w(0.33) \cdot v^{PT}(2500) + w(0.66) \cdot v^{PT}(2400) + w(0.01) \cdot v^{PT}(0) \tag{3.8}$$

$$< w(1.00) \cdot v^{PT}(2400) = u^{PT}(1B), \tag{3.9}$$

and

$$u^{PT}(2A) = w(0.33) \cdot v^{PT}(2500) > w(0.34) \cdot v^{PT}(2400) = u^{PT}(2B) \tag{3.10}$$

are established simultaneously.

Here, we confirmed the main two effects of PT. PWE captures the feature that people often over-weight low probabilities and under-weight moderate and high probabilities. And FE captures the effect of loss aversion on people, i.e., the same amount of loss usually looms larger than the same amount of gain to a person.

Chapter 4

Psychophysics Experiment

As we already discussed in Chapter 2, there were various attempts to understand the end-users' quality of experience (QoE) [53–56]: however, there have been none that used psychophysics methodology to estimate the probability weighting function (PWF) for Prospect Theory (PT). Therefore, in this chapter, we perform psychophysics experiments [61] to determine the relationship between end-users' QoE and wireless network's QoS (quality of service). From the observed results, we can numerically estimate the parameter α of Prelec's PWF (Equation 3.3).

4.1 Experiment Design

4.1.1 Testbed and Overview

The experiment was conducted using a testbed shown in Figure 4.1 with human subjects. Each subject was asked to watch a 1 hour video that was streamed over wireless channels. The testbed comprises a single compute/communication device (the programmable ORBIT radio node [62]) with two major software components (i) a network emulation module (NETEM), and (ii) a content caching module. The radio modem in the ORBIT node was used to implement a soft access point that transmits WiFi signals. All the traffic going through the access point was subject to traffic shaping policies as specified in the NETEM module, specifically to control wireless network performance in terms of packet loss and delay. To alleviate the artifacts of wide area internet connectivity on the experimental conditions, we created a local caching functionality in the platform. A one hour video was divided into 30 2-minute segments and each segment of the video was subject to a different one of 30 control parameter combinations involving packet loss and delay. Also, video was streamed without cache memory so that the streaming quality reflected the wireless network performance in real-time. While watching the video, subjects evaluated the streaming quality of each segment. The human subject interface device is a laptop used to watch the streaming video.

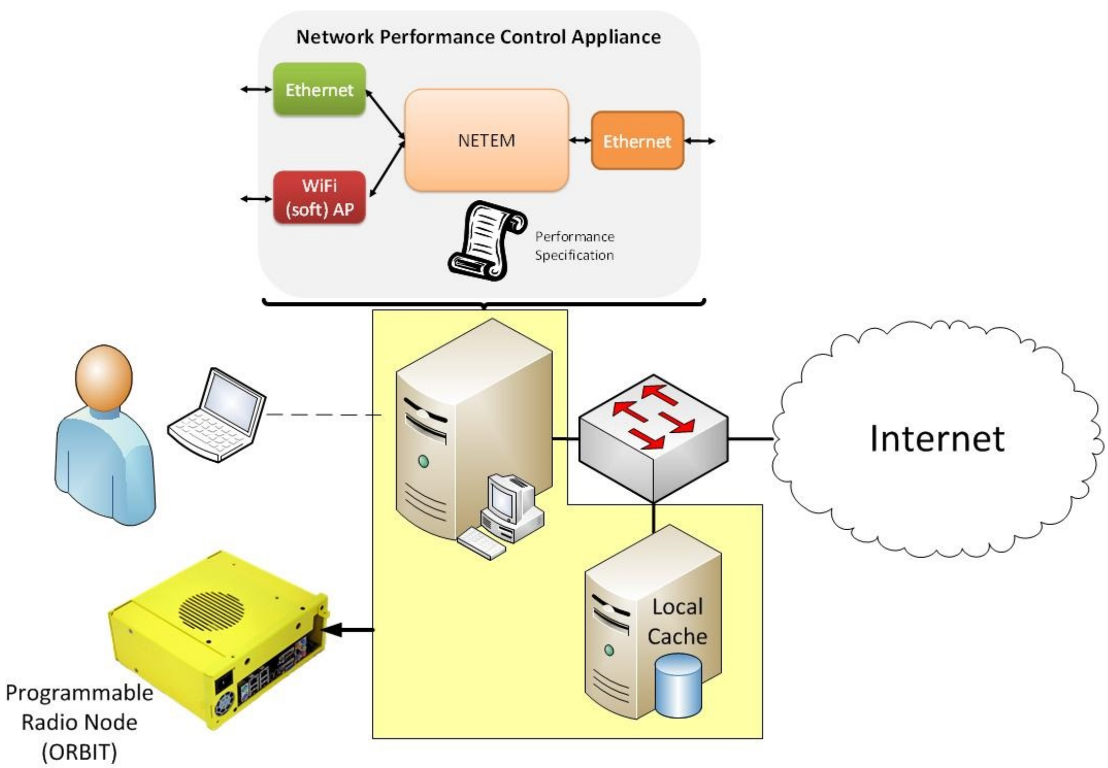


Figure 4.1 Experimental platform illustration

4.1.2 Objective Metric: Video Streaming QoS over Wireless Channels

To measure video streaming quality of service (QoS), we used VLC player [63] in our experiment platform and collected the log of video streaming statistics. From the log, we calculated the decoded frames per second (FPS), which is our objective metric of video QoS. (Other statistics calculated from the log are included in Appendix A.) Because decoded FPS is directly related to the number of stops and stutters of streaming video, it measures the uncertainty of wireless network performance on video QoS. Collected measurements of decoded FPS were mapped to objective probabilities (p) of Prelec's probability weighting function (PWF) (Equation 3.3). Note that the parameters, delay and packet loss, were not the objective measurements of WiFi QoS in our experiment design. They were control parameters used to create variations of WiFi QoS, and hence video QoS over the wireless channels.

4.1.3 Subjective Metric: User Ratings of Video Streaming QoS

To measure human subject's perception of video QoS over wireless channels, a four level scaled rating chart was provided to subjects as follows.

- Excellent: No complaints.
- Good: Can definitely sit through the video, but the quality does detract a bit of enjoyment.
- Satisfactory: Can sit through the video at this quality, but it might be annoying.
- Unacceptable: Cannot watch anymore/Cannot bear to sit through this quality.

Each rating scale of this list corresponded to a quantitative score: 4, 3, 2, 1 respectively. Ratings were mapped to subjective probabilities($w(p)$) of Prelec's PWF.

4.2 Experiments

4.2.1 Phase 1-1: College Students, Laptop Screen (17.3-inch)

We recruited 23 college students from the Psychology department of Rutgers University for the first phase of our psychophysics experiment. A movie list was provided to each subject, and he/she selected which movie to watch. And the video was viewed on a laptop screen (17.3-inch). This experiment was conducted during the Spring semester, 2015.

4.2.2 Phase 1-2: Community Residents, Laptop Screen (17.3-inch)

To avoid biased subject group and generalize our experiment, we recruited 25 adult members from a local church to participate in the same experiment. This experiment was conducted during the Spring semester, 2016.

4.2.3 Phase 2: College Students, Large TV Screen (70-inch)

One purpose of this experiment was to collect more data from each subject to increase the precision of the fit to Prelec's PWF (Equation 3.3). Another purpose was to generalize to another video presentation device. We recruited 27 college students from Psychology department of Rutgers University again. This time, each subject watched 4 given movies without their choice (a total 4 hours): the collected data set size for each student was four times that of phase 1-1 or 1-2, so we were able to observe the parameter (α of Prelec's PWF) variations by human subject and movie genre. Additionally, subjects watched movies on a large TV screen (70-inch). So we tested multiple subjects simultaneously. This experiment was conducted during the Fall semester, 2015.

Chapter 5

Data Analysis and Discussions

5.1 Phase 1-1: College Students, Laptop Screen (17.3-inch)

- Subject group: 23 college students
- Each subject selected which movie to watch from the list
- Subject interface device: laptop screen (17.3-inch)

5.1.1 Raw Measurements

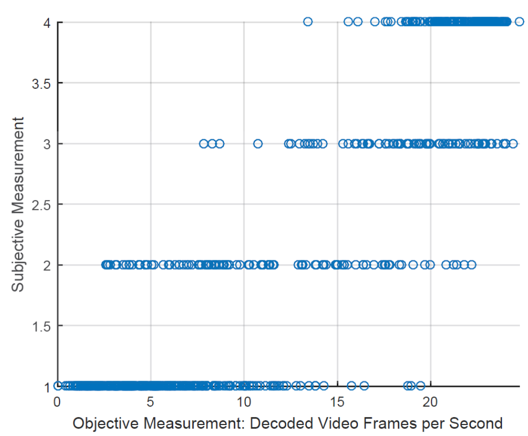


Figure 5.1 Raw data: a total 690 data points = 23 subjects × 30 segments

Using the experiment platform, we calculate the average decoded FPS for each 2-minute segment. Also, each segment had a subjective rating with 4 (Excellent) being the highest rating and 1 (Unacceptable) being the lowest rating. We had a total 23 subjects for this phase and each subject evaluated 30 segments, therefore the raw data set had a total 690 data points (Figure 5.1).

5.1.2 Averaged Data Set over Parameter Combinations

Subjective Ratings

Packet Loss (%)	**0**		**2**		**4**		**8**		**16**	
Delay (ms)	**mean**	dev	**mean**	dev	**mean**	dev	**mean**	dev	**mean**	dev
0	**3.67**	0.64	**3.71**	0.56	**3.60**	0.58	**3.16**	1.02	**1.29**	0.45
20	**3.80**	0.40	**2.89**	1.15	**2.66**	1.10	**1.54**	0.77	**1.16**	0.36
40	**3.82**	0.48	**2.00**	0.85	**1.54**	0.86	**1.27**	0.54	**1.10**	0.30
60	**3.58**	0.76	**1.71**	0.87	**1.34**	0.57	**1.25**	0.54	**1.21**	0.52
80	**3.69**	0.71	**1.40**	0.77	**1.21**	0.41	**1.10**	0.44		
160	**3.53**	0.63	**1.17**	0.48	**1.24**	0.64				
320	**2.65**	0.92	**1.10**	0.29						
640	**1.87**	0.99								

Decoded Video Frames per Second

Packet Loss (%)	**0**		**2**		**4**		**8**		**16**	
Delay (ms)	**mean**	dev	**mean**	dev	**mean**	dev	**mean**	dev	**mean**	dev
0	**21.28**	1.79	**21.50**	1.81	**21.27**	1.83	**19.67**	3.30	**5.32**	2.46
20	**21.55**	1.50	**18.01**	4.87	**15.28**	5.39	**9.26**	4.10	**3.39**	2.77
40	**21.84**	1.43	**13.33**	4.97	**9.79**	3.71	**5.11**	2.59	**2.90**	1.79
60	**20.92**	4.34	**10.28**	5.08	**7.54**	3.70	**5.74**	4.34	**2.47**	1.70
80	**21.62**	1.60	**7.50**	4.22	**5.48**	3.08	**3.65**	2.44		
160	**20.14**	2.53	**4.66**	2.48	**3.94**	4.10				
320	**16.97**	4.39	**3.67**	1.74						
640	**11.71**	4.94								

Figure 5.2 Averaged raw measurements by parameter combinations along with their means and standard deviations: upper table as subjective measurements and lower table as objective measurements

Averaging the raw data points over each pair of packet loss and delay chosen, Figure 5.2 shows the mean and standard deviation for the objective (decoded video frames per second) and the subjective (on a scale of 1-4) measurements. The best wireless channel quality corresponds to the unit in the upper left corner, where no packet loss and delay are present. The worst wireless channel qualities being rated are the units just above the blackened out units. The blackened out area of the tables includes the

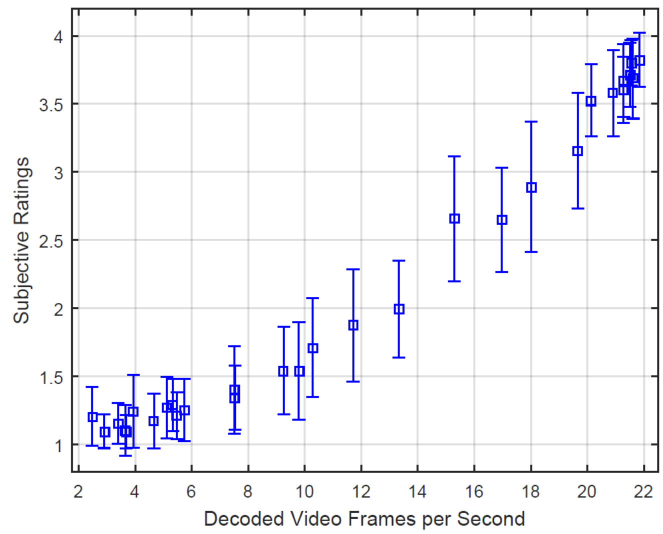


Figure 5.3 Quality of service (QoS) ratings shown as a function of decoded video frames per second with 95% confidence level.

parameter values for which the quality of the wireless channel is so poor that there is no video displayed in the player. The average subjective ratings (Figure 5.2) reveals that there is tendency of the human subjects to "underweight" the best (even perfect) video quality and "overweight" the worst case video quality. This effect can also be observed explicitly in Figure 5.3, where we show the relationship between the subjective rating and the objective metric with 95% confidence level.

5.1.3 Normalizing Metrics to Probabilities

As we discussed in Chapter 4, our objective measurements in Figure 5.3 are directly related to the number of stops and stutters of streaming video. Thus we can map this objective metric directly as a proxy for the objective probabilities of PWE in terms of uncertainty of wireless channel performance. The subjective measurements in Figure 5.3 are the subjective perception of streaming video QoS. In order to observe the relationship between objective and subjective probabilities of PWE, we used a simple uniform normalization, i.e. dividing by the maximum value, from objective/subjective measurements to the objective/subjective probabilities in region $[0, 1]$. In Figure 5.4, we can observe the data points mapped to $[0, 1] \times [0, 1]$ following from Figure 5.3.

5.1.4 Fitting Normalized Data Set to Probability Weighting Function

Normalizing averaged measurements into probabilities, we fit them to a parametric function of Prelec's PWF (Equation 3.3), then the estimated parameter α that minimizes the mean-squared error (MSE) is found to be $\alpha \approx 0.6117$ ($MSE \approx 0.0015$). The result is depicted in Figure 5.4, where we obtain the probability of each frame being displayed successfully as the horizontal axis: p, and the probability of the human subject believing that the video is uninterrupted as the vertical axis: $w(p)$. The relationship between these two variables reveals that the result of this experiment follows Prelec's PWE, an inverse S-shaped probability weighting effect.

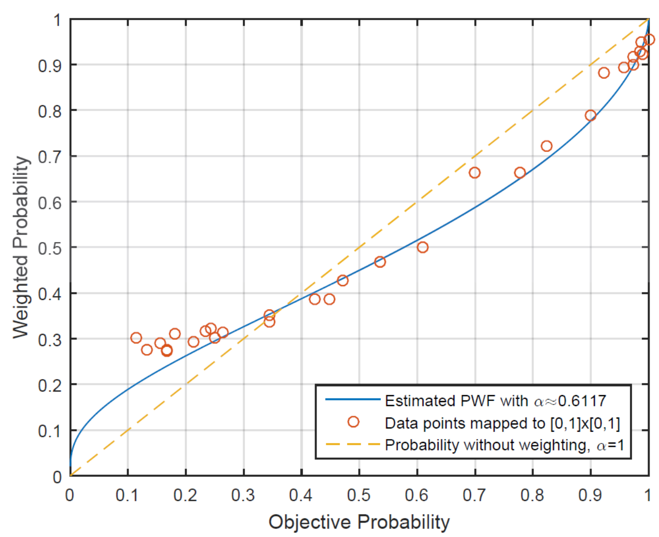


Figure 5.4 Psychophysics experiment (phase 1-1): college students, laptop screen (17.3")
The probability weighting effect (PWE) can be well approximated with Prelec's probability weighting function (PWF) with $\alpha \approx 0.6117$ that minimizes the mean-squared error to ($MSE \approx 0.0015$).

5.2 Phase 1-2: Community Residents, Laptop Screen (17.3-inch)

- Subject group: 25 adult members of a local church
- Average age of subject group: 46.77 (standard deviation 9.32)
- Each subject selected which movie to watch from the list
- Subject interface device: laptop screen (17.3-inch)

Following the same analysis with phase 1-1, results are depicted in Figure 5.5. The estimated parameter ($\alpha \approx 0.7049$) of this elder subject group is slightly bigger than that ($\alpha \approx 0.6117$) of college student group. Thus we can conclude that the elder people are less sensitive about the video QoS than college students are; however, Prelec's PWE is still preserved for the elder subject group.

5.3 Phase 2: College Students, Large TV screen (70-inch)

- Subject group: 27 college students
- Each subject watched 4 given movies
  - The Dark Knight 1080p (file size: 18.2 MB/minute)
  - Frozen 720p (file size: 16.1 MB/minute)
  - Sherlock Holmes 720p (file size: 5.6 MB/minute)
  - Inception 1080p (file size: 13.1 MB/minute)
- Subject interface device: large TV screen (70-inch)
- Several parameter combinations of delay and packet loss which produced worst video QoS are replaced with more moderate combinations to provide a more sensitive range of video QoS.

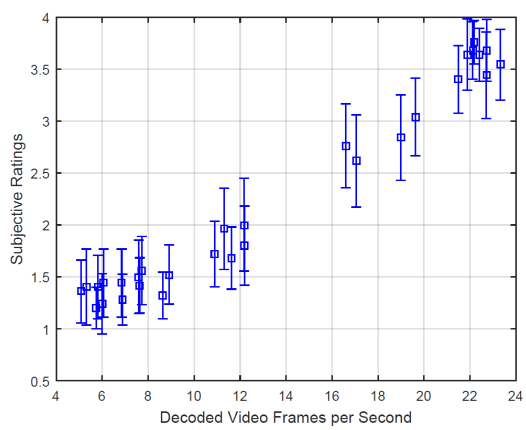
Subjective Ratings

Packet Loss (%)	0		2		4		8		16	
Delay (ms)	mean	dev	mean	dev	mean	dev	mean	dev	mean	dev
0	**3.44**	1.04	**3.68**	0.69	**3.76**	0.52	**3.04**	0.93	**1.50**	0.91
20	**3.68**	0.75	**2.84**	1.03	**2.76**	1.01	**1.96**	0.98	**1.20**	0.50
40	**3.54**	0.83	**1.80**	0.96	**1.68**	0.75	**1.56**	0.82	**1.36**	0.76
60	**3.64**	0.64	**1.72**	0.79	**1.52**	0.71	**1.40**	0.76	**1.24**	0.72
80	**3.64**	0.86	**1.32**	0.56	**1.44**	0.82	**1.44**	0.82		
160	**3.40**	0.82	**1.28**	0.61	**1.40**	0.91				
320	**2.62**	1.13	**1.42**	0.65						
640	**2.00**	1.12								

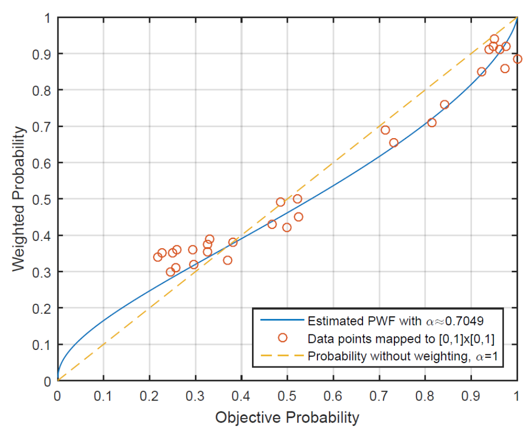
Decoded Video Frames per Second

Packet Loss (%)	0		2		4		8		16	
Delay (ms)	mean	dev	mean	dev	mean	dev	mean	dev	mean	dev
0	**22.71**	1.92	**22.12**	2.11	**22.19**	1.88	**19.63**	5.33	**7.58**	4.98
20	**22.73**	1.77	**19.00**	4.54	**16.60**	5.31	**11.31**	4.34	**5.74**	3.96
40	**23.31**	1.55	**12.20**	4.60	**11.63**	4.67	**7.73**	2.88	**5.07**	5.10
60	**22.41**	1.83	**10.89**	3.98	**8.90**	3.50	**5.80**	4.02	**5.99**	6.39
80	**21.89**	4.90	**8.63**	4.30	**6.85**	4.13	**6.06**	3.44		
160	**21.49**	2.99	**6.88**	3.36	**5.31**	4.23				
320	**17.04**	5.06	**7.62**	4.71						
640	**12.17**	6.82								

(a) Averaged raw measurements by parameter combinations along with their means and standard deviations



(b) Averaged data with 95% confidence interval



(c) Fitting normalized data points to PWF

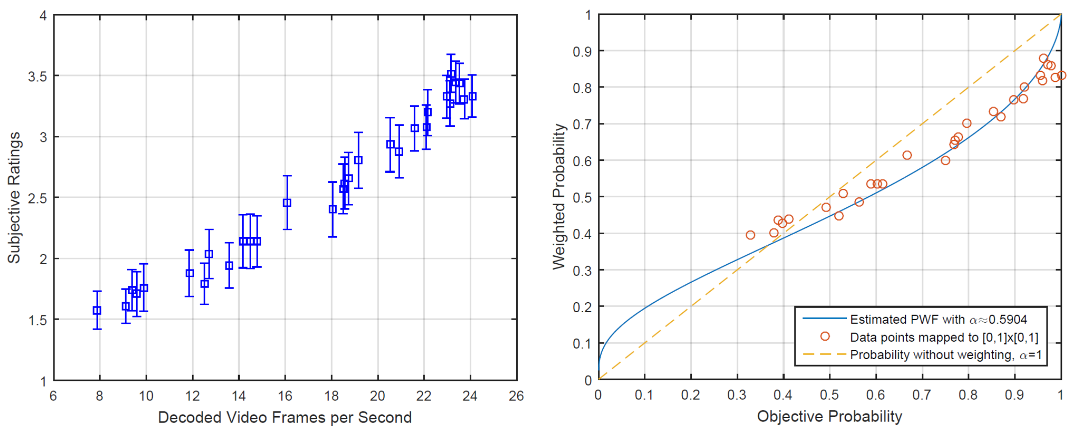
Figure 5.5 Psychophysics experiment (phase 1-2): community residents, laptop screen (17.3") Average age of subject group was 46.77 with standard deviation 9.32. Each subject selected which movie to watch from the list. Estimated Prelec's parameter is $\alpha \approx 0.7049$ that minimizes mean-squared error to ($MSE \approx 0.0021$).

Following the same analysis with previous phases, results are depicted in Figure 5.6. The estimated parameter ($\alpha \approx 0.5904$) was almost the same with the first phase ($\alpha \approx 0.6117$), thereby we confirmed the generality of Prelec's PWE in our experiment platform, i.e. the screen size barely makes any variation of parameter (α). Note that the data size of this phase is bigger than four times of that of phase 1-1 or 1-2.

Subjective Ratings												
Packet Loss (%)	0		1		2		4		8		16	
Delay (ms)	mean	dev	mean	dev	mean	dev	mean	dev	mean	dev	mean	dev
0	**3.45**	0.88	**3.33**	0.88	**3.52**	0.80	**3.31**	0.83	**3.07**	0.95	**1.71**	0.94
20	**3.43**	0.86	**2.93**	1.14	**2.88**	1.12	**2.62**	1.10	**2.14**	1.09	**1.58**	0.74
40	**3.27**	0.97	**2.81**	1.14	**2.40**	1.17	**1.94**	0.96	**1.61**	0.74		
60	**3.33**	0.91	**2.65**	1.11	**2.14**	1.15	**1.88**	0.99				
80	**3.08**	0.94	**2.46**	1.14	**2.04**	1.04						
160	**3.20**	0.97	**1.79**	0.86	**1.76**	0.95						
320	**2.57**	1.06	**1.74**	0.82								
640	**2.14**	1.12										

Decoded Video Frames per Second												
Packet Loss (%)	0		1		2		4		8		16	
Delay (ms)	mean	dev	mean	dev	mean	dev	mean	dev	mean	dev	mean	dev
0	**23.36**	2.54	**24.07**	0.98	**23.16**	3.23	**23.74**	1.15	**21.58**	3.98	**9.58**	5.38
20	**23.52**	2.23	**20.52**	5.24	**20.93**	4.19	**18.58**	5.04	**14.78**	5.87	**7.88**	4.90
40	**23.12**	2.90	**19.17**	5.37	**18.05**	5.45	**13.58**	5.38	**9.12**	4.01		
60	**22.97**	3.26	**18.73**	5.74	**14.49**	6.89	**11.85**	6.78				
80	**22.09**	3.14	**16.08**	7.17	**12.72**	6.58						
160	**22.15**	4.25	**12.51**	4.95	**9.88**	5.45						
320	**18.49**	5.19	**9.37**	6.07								
640	**14.18**	6.30										

(a) Averaged raw measurements by parameter combinations along with their means and standard deviations

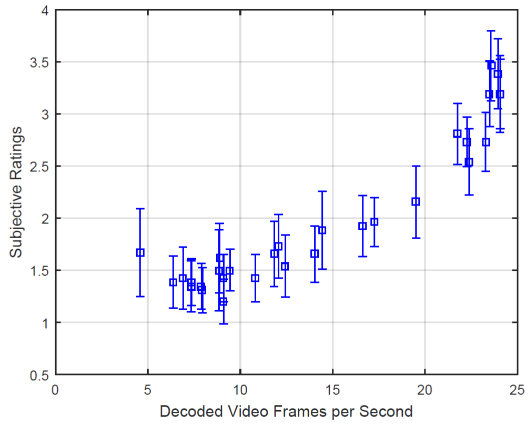


(b) Averaged data with 95% confidence interval (c) Fitting normalized data points to PWF

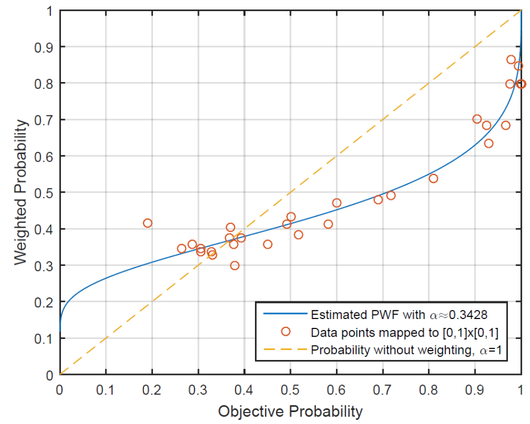
Figure 5.6 Psychophysics experiment (phase 2): college students, large TV screen (70") Each subject watched 4 given movies without their choice. Estimated Prelec's parameter is $\alpha \approx 0.5904$ that minimizes mean-squared error to ($MSE \approx 0.0021$).

5.3.1 Analysis by Each Movie

We analyzed the data set for each movie. Results are depicted in Figure 5.7, Figure 5.8, Figure 5.9 and Figure 5.10. (Measurement tables are depicted in Appendix B.) There was interesting parameter α variation by movies. Action movies such as The Dark Knight 1080p ($\alpha \approx 0.3482$, Figure 5.7) and Inception 1080p ($\alpha \approx 0.4847$, Figure

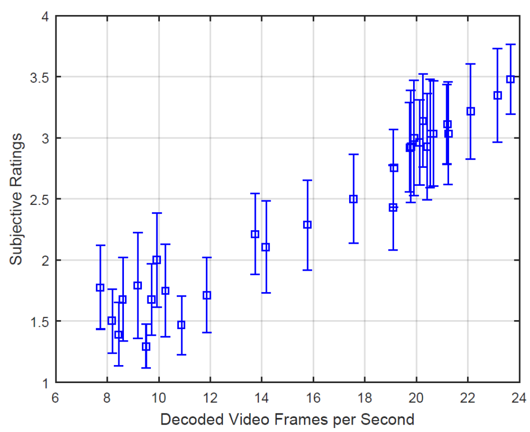


(a) Averaged data with 95% confidence interval

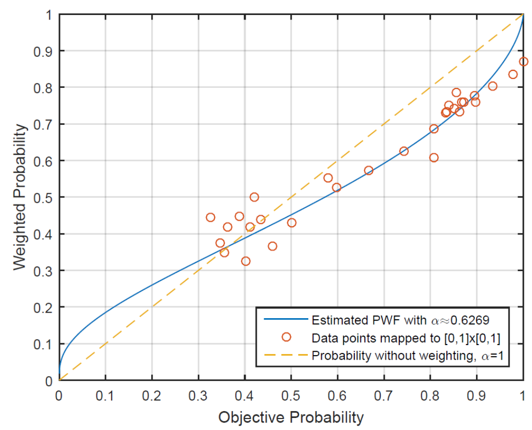


(b) Fitting normalized data points to PWF

Figure 5.7 Psychophysics experiment (phase 2): The Dark Knight 1080p (18.2 MB/minute) Estimated Prelec's parameter is $\alpha \approx 0.3428$ that minimizes mean-squared error to ($MSE \approx 0.0034$).



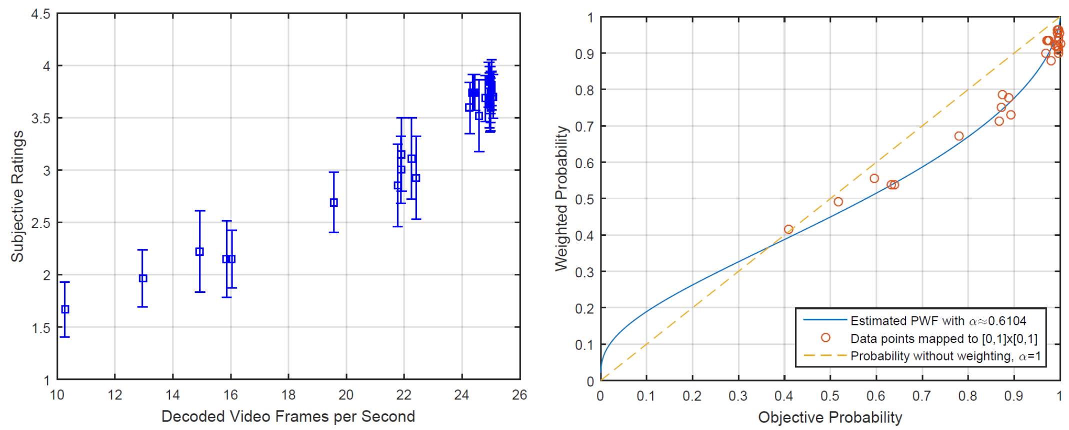
(a) Averaged data with 95% confidence interval



(b) Fitting normalized data points to PWF

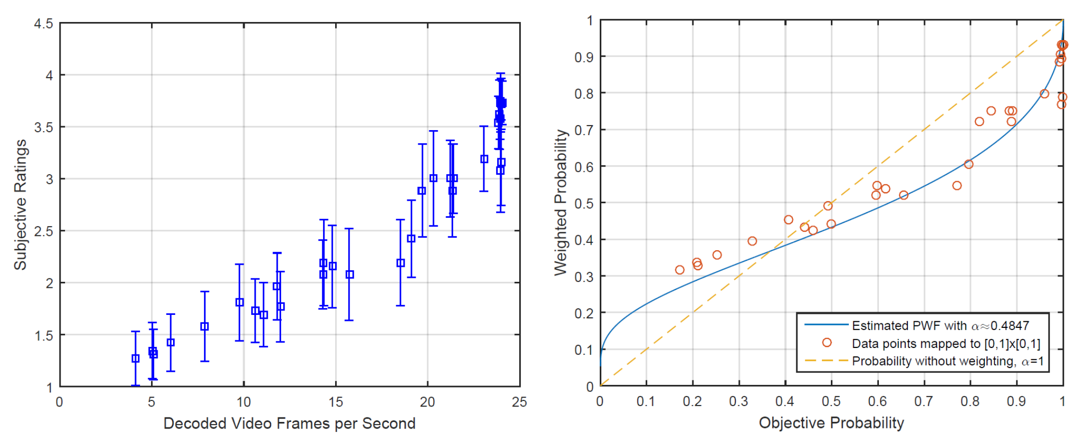
Figure 5.8 Psychophysics experiment (phase 2): Frozen 720p (16.1 MB/minute) Estimated Prelec's parameter is $\alpha \approx 0.6269$ that minimizes mean-squared error to ($MSE \approx 0.0025$).

5.10) have relatively low parameter α values. On the other hand, non-action movie such as Sherlock Holmes 720p ($\alpha \approx 0.6104$, Figure 5.9) and animation movie such as Frozen 720p ($\alpha \approx 0.6269$, Figure 5.8) have relatively high parameter α values. Subjects were much more sensitive about the streaming qualities of fast-scene-changing movies while they were less sensitive to slow-scene-changing movies, which implies that the



(a) Averaged data with 95% confidence interval (b) Fitting normalized data points to PWF

Figure 5.9 Psychophysics experiment (phase 2): Sherlock Holmes 720p (5.6 MB/minute) Estimated Prelec's parameter is $\alpha \approx 0.6104$ that minimizes mean-squared error to ($MSE \approx 0.0012$).

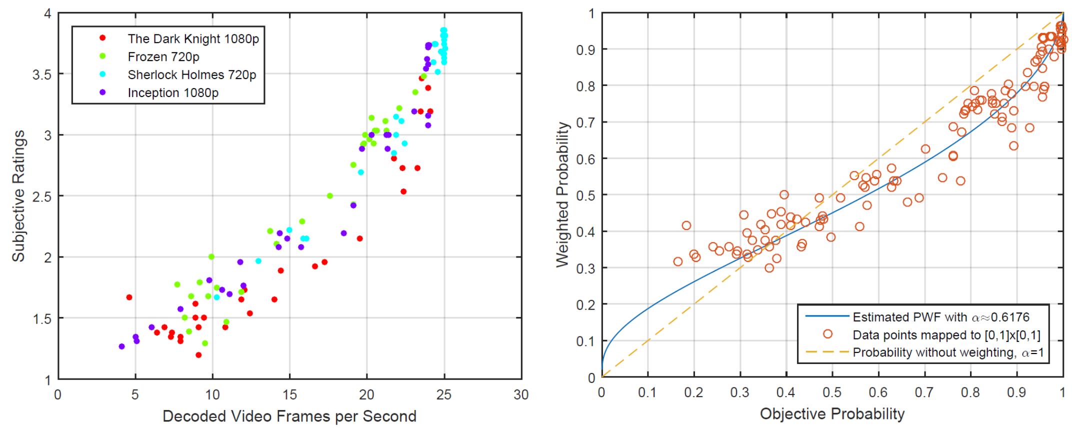


(a) Averaged data with 95% confidence interval (b) Fitting normalized data points to PWF

Figure 5.10 Psychophysics experiment (phase 2): Inception 1080p (13.1 MB/minute) Estimated Prelec's parameter is $\alpha \approx 0.4847$ that minimizes mean-squared error to ($MSE \approx 0.0039$).

end-user's perception of wireless service is influenced by the contents.

Merging analyses of the 4 movies together ($\alpha \approx 0.6176$, Figure 5.11), we can observe the PWE more explicitly than any other analysis, there is tendency of the human subjects to "underweight" nicely guaranteed (even perfect) quality and "overweight" the worst case uncertainty.



(a) Divide averaged data points by movies (b) Fitting normalized data points to PWF

Figure 5.11 Psychophysics experiment (phase 2): 4 movies altogether
Estimated Prelec's parameter is $\alpha \approx 0.6167$ with $MSE \approx 0.0031$.

5.3.2 Analysis by Each Subject

We also analyzed the data set by each subject. The distribution of parameter α over the 27 participants in phase 2 is shown in Figure 5.12. It shows that the parameter α follows the normal distribution.

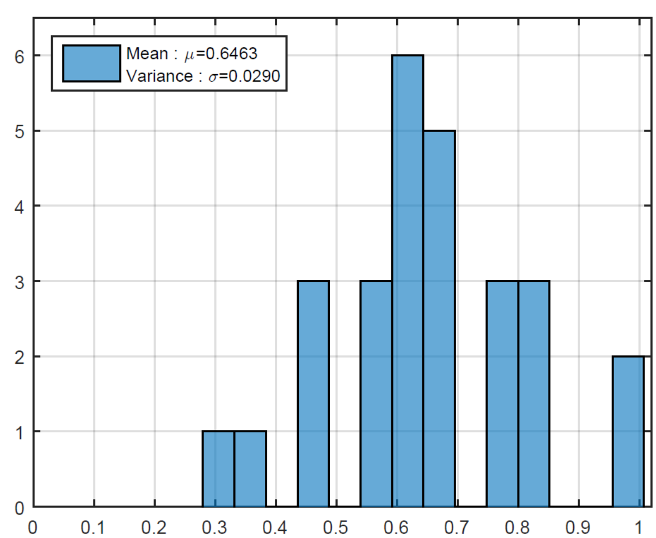


Figure 5.12 Distribution of parameter α over 27 subjects in phase 2: mean=0.65, variance=0.029

Chapter 6

Conclusions and Future Works

In this thesis, we performed psychophysics experiments to assess end-user perception of video QoS over wireless channels. We confirmed the probability weighting effect (PWE) of Prospect Theory (PT) in the QoE of wireless network services. Note that there have been efforts to subjectively evaluate video QoS [64] that have used various technical measures such as peak signal to noise ratio (PSNR) but there have been none that used psychophysics methodology to estimate the probability weighting function (PWF) for Prospect Theory (PT) as undertaken here. [61], which includes phase 1-1 results, is the first such effort and phase 1-2 and phase 2 are additionally reported here. From these human subject studies, we conclude:

- There is general tendency of the end-users to "underweight" nicely guaranteed (even perfect) quality and "overweight" the worst case uncertainty in wireless QoS.
- This tendency (PWE) follows Prelec's PWF (Equation 3.3).
- Significant difference in screen size (17.3-inch vs 70-inch) barely makes any variation of Prelec's parameter (α).
- Although the general tendency of PWE is preserved, specific parameter value varies depending on video content and individual subject.

- Distribution of Prelec's parameter α follows the normal distribution across subjects.

This research can be further expanded to include more detailed mapping techniques to normalize objective and subjective measurements to the corresponding probabilities of service guarantees (uncertainty). Such psychophysics studies can also be conducted by the wireless service providers (SP) for learning each individual end-user's subjective perceptions to objective metrics and can be implemented via appropriate "apps" on end-user devices such as smart phones. Then they would be able to identify how their price offerings and resource allocation mechanisms impact the "value" of that resource to end-users and conversely, how end-user behavior impacts resource allocation, thereby understanding the game-theoretical interplay between the SPs and the end-users. Thus, the findings here and future works will provide useful pointers for designing optimal pricing schemes and resource management algorithms in wireless networks to manage the ever increasing demand for data.

Appendix A

VLC Statistics Field

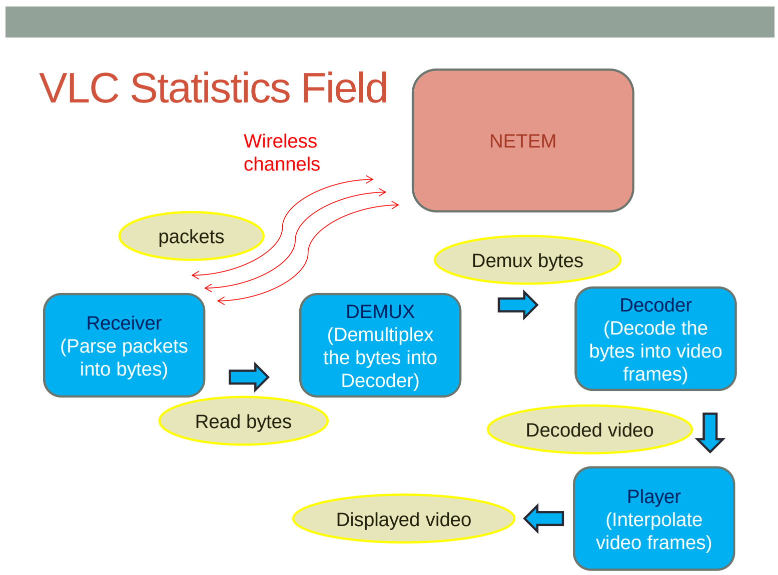
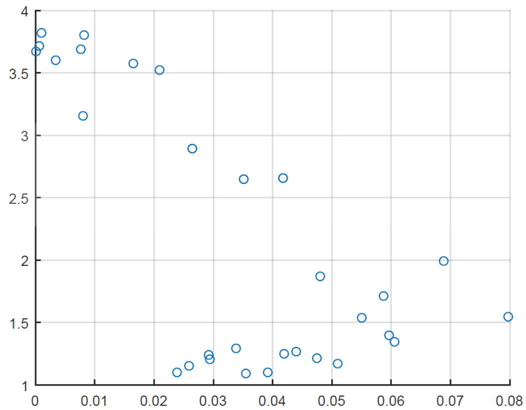
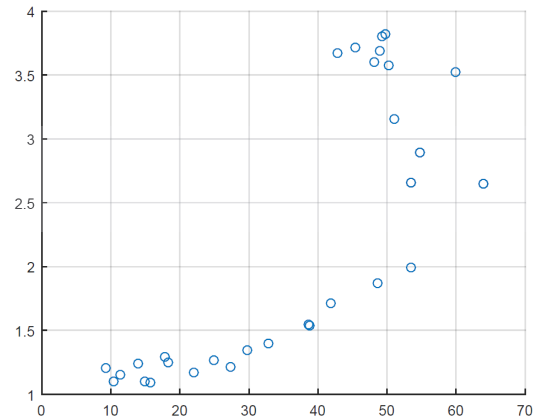


Figure A.1 Illustration of VLC player statistics. See also Figure A.2.

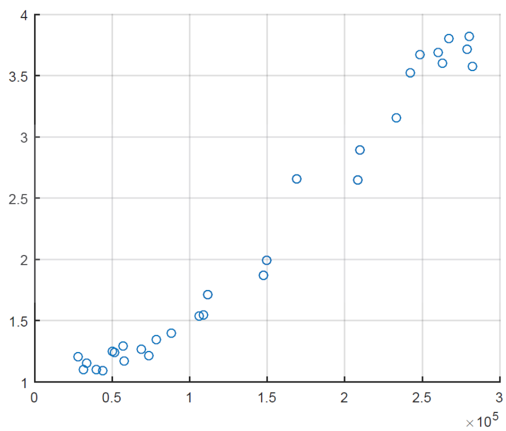
- read packets: number of video packets delivered to VLC player over wireless channel
- read bytes: number of bytes parsed from the delivered video packets
- demux bytes: number of bytes demultiplexed into the decoder
- decoded video frames: number of video frames decoded from the decoder
- displayed pictures: number of video frames after interpolating the decoded frames
- lost pictures: number of lost video frames



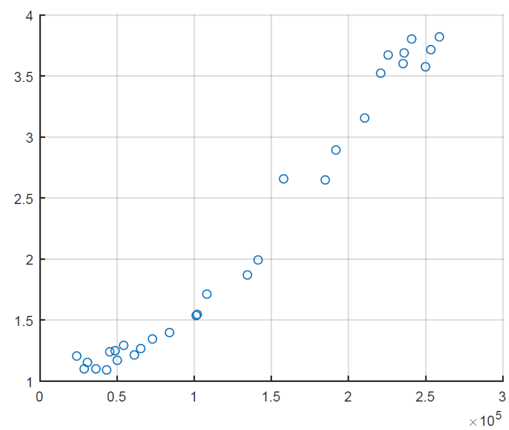
(a) Lost video frames (per second)



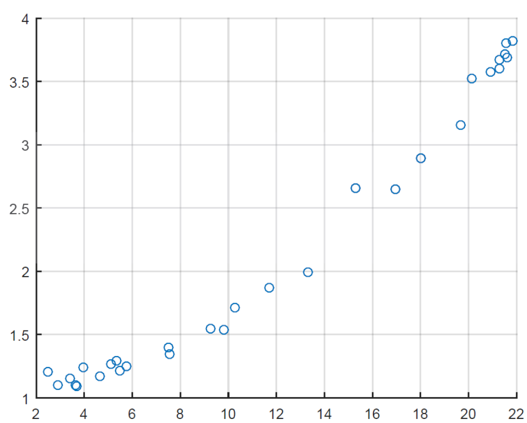
(b) Read packets (per second)



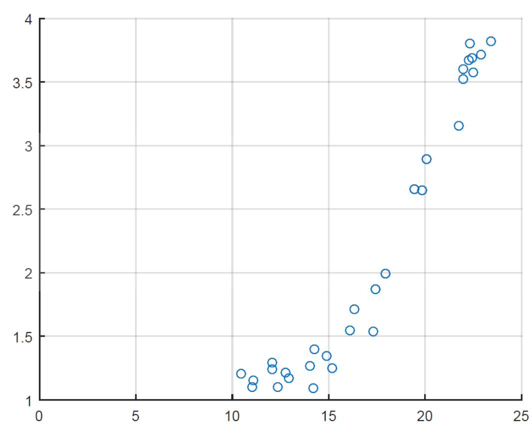
(c) Read bytes (per second)



(d) Demultiplexed bytes into the decoder (per second)



(e) Video frames decoded from the decoder (per second)



(f) Video frames after interpolating the decoded frames (per second)

Figure A.2 Subjective ratings of video QoS (vertical axis) shown as a function of several VLC statistics (horizontal axis).

Appendix B

Analysis by Each Movie: Measurement Tables

Subjective Ratings

Packet Loss (%)	0		1		2		4		8		16	
Delay (ms)	mean	dev	mean	dev	mean	dev	mean	dev	mean	dev	mean	dev
0	3.19	0.94	3.19	0.85	3.46	0.86	2.73	0.60	1.96	0.60	1.62	0.85
20	3.38	0.85	1.65	0.69	1.92	0.74	1.73	0.78	1.31	0.55	1.50	0.67
40	2.73	0.72	1.65	0.80	1.54	0.76	1.50	0.51	1.38	0.57		
60	3.19	0.80	1.42	0.58	1.35	0.56	1.38	0.64				
80	2.54	0.81	1.42	0.76	1.35	0.63						
160	2.81	0.75	1.42	0.58	1.20	0.41						
320	2.15	0.88	1.67	0.82								
640	1.88	0.95										

Decoded Video Frames per Second

Packet Loss (%)	0		1		2		4		8		16	
Delay (ms)	mean	dev	mean	dev	mean	dev	mean	dev	mean	dev	mean	dev
0	24.06	0.18	24.08	0.79	23.57	0.55	22.28	0.93	17.26	1.20	8.88	2.29
20	23.94	0.24	14.03	1.65	16.63	3.38	12.07	2.00	7.95	1.42	8.85	7.88
40	23.28	0.73	11.83	1.89	12.44	2.09	9.44	1.16	7.36	2.16		
60	23.49	0.90	10.82	2.52	7.89	2.77	6.37	3.27				
80	22.39	1.68	6.90	1.26	7.33	2.41						
160	21.75	2.37	9.10	2.49	9.10	3.46						
320	19.52	2.59	4.58	0.56								
640	14.44	4.03										

Figure B.1 Phase 2 measurement tables: The Dark Knight 1080p

Subjective Ratings

Packet Loss (%)	0		1		2		4		8		16	
Delay (ms)	mean	dev	mean	dev	mean	dev	mean	dev	mean	dev	mean	dev
0	3.04	1.17	3.35	0.98	3.14	1.01	3.48	0.71	2.96	0.92	1.79	1.06
20	3.04	1.09	3.00	1.20	3.04	1.14	2.75	0.84	2.11	0.99	1.78	0.89
40	2.93	1.15	3.11	0.85	2.43	0.92	1.71	0.81	1.50	0.69		
60	2.93	1.21	2.50	0.96	1.46	0.64	1.39	0.69				
80	2.92	0.93	2.21	0.88	1.68	0.77						
160	3.21	1.03	1.30	0.47	2.00	1.02						
320	2.29	0.98	1.68	0.90								
640	1.75	1.00										

Decoded Video Frames per Second

Packet Loss (%)	0		1		2		4		8		16	
Delay (ms)	mean	dev	mean	dev	mean	dev	mean	dev	mean	dev	mean	dev
0	20.53	3.66	23.14	1.17	20.26	5.23	23.66	0.72	20.13	4.87	9.19	4.69
20	21.23	3.45	19.90	5.99	20.66	3.63	19.11	3.11	14.17	3.74	7.74	5.91
40	20.41	4.54	21.18	2.24	19.09	1.77	11.86	2.05	8.19	1.42		
60	19.78	5.04	17.56	2.59	10.88	2.22	8.44	3.34				
80	19.73	3.77	13.74	4.39	9.71	3.00						
160	22.10	1.52	9.51	1.76	9.93	5.18						
320	15.77	4.13	8.61	5.63								
640	10.25	4.33										

Figure B.2 Phase 2 measurement tables: Frozen 720p

Subjective Ratings												
Packet Loss (%)	**0**		**1**		**2**		**4**		**8**		**16**	
Delay (ms)	**mean**	dev	**mean**	dev	**mean**	dev	**mean**	dev	**mean**	dev	**mean**	dev
0	**3.85**	0.36	**3.70**	0.54	**3.78**	0.42	**3.85**	0.36	**3.74**	0.53	**2.15**	0.95
20	**3.59**	0.57	**3.85**	0.36	**3.63**	0.69	**3.74**	0.45	**2.93**	1.04	**1.67**	0.68
40	**3.81**	0.62	**3.68**	0.48	**3.52**	0.89	**2.85**	1.03	**1.96**	0.71		
60	**3.67**	0.68	**3.67**	0.55	**3.59**	0.64	**3.00**	0.83				
80	**3.81**	0.56	**3.74**	0.45	**3.15**	0.91						
160	**3.85**	0.46	**2.69**	0.74	**2.22**	1.01						
320	**3.74**	0.45	**2.15**	0.72								
640	**3.11**	1.01										

Decoded Video Frames per Second												
Packet Loss (%)	**0**		**1**		**2**		**4**		**8**		**16**	
Delay (ms)	**mean**	dev	**mean**	dev	**mean**	dev	**mean**	dev	**mean**	dev	**mean**	dev
0	**24.97**	0.11	**25.07**	0.13	**25.01**	0.11	**24.98**	0.16	**24.98**	0.08	**15.86**	2.87
20	**24.98**	0.04	**24.96**	0.07	**24.97**	0.09	**24.37**	1.06	**22.41**	2.00	**10.27**	2.36
40	**25.03**	0.19	**24.80**	0.11	**24.59**	1.50	**21.77**	2.33	**12.95**	4.98		
60	**24.94**	0.16	**24.98**	0.16	**24.26**	0.80	**21.88**	2.45				
80	**24.91**	0.11	**24.44**	0.45	**21.91**	3.55						
160	**24.95**	0.10	**19.57**	2.83	**14.94**	4.64						
320	**24.38**	0.77	**16.04**	4.13								
640	**22.26**	4.38										

Figure B.3 Phase 2 measurement tables: Sherlock Holmes 720p

Subjective Ratings												
Packet Loss (%)	**0**		**1**		**2**		**4**		**8**		**16**	
Delay (ms)	**mean**	dev	**mean**	dev	**mean**	dev	**mean**	dev	**mean**	dev	**mean**	dev
0	**3.73**	0.28	**3.08**	1.03	**3.72**	0.38	**3.15**	1.10	**3.58**	0.25	**1.27**	0.44
20	**3.73**	0.52	**3.19**	0.64	**2.88**	1.31	**2.19**	1.12	**2.19**	1.12	**1.31**	0.38
40	**3.62**	0.73	**3.00**	1.36	**2.08**	1.27	**1.69**	0.62	**1.58**	0.73		
60	**3.54**	0.42	**3.00**	0.72	**2.15**	1.02	**1.73**	0.60				
80	**3.00**	0.88	**2.42**	0.89	**1.96**	0.68						
160	**2.88**	1.31	**1.77**	0.74	**1.35**	0.48						
320	**2.08**	0.71	**1.42**	0.49								
640	**1.81**	0.88										

Decoded Video Frames per Second												
Packet Loss (%)	**0**		**1**		**2**		**4**		**8**		**16**	
Delay (ms)	**mean**	dev	**mean**	dev	**mean**	dev	**mean**	dev	**mean**	dev	**mean**	dev
0	**24.03**	0.17	**23.95**	0.18	**23.98**	0.10	**23.98**	0.24	**23.93**	0.22	**4.11**	3.14
20	**23.95**	0.10	**23.04**	1.86	**21.33**	3.39	**18.50**	3.42	**14.34**	3.59	**5.09**	1.81
40	**23.90**	0.13	**20.29**	4.16	**15.73**	5.49	**11.07**	3.31	**7.89**	3.74		
60	**23.83**	0.20	**21.40**	3.10	**14.81**	4.94	**10.61**	3.39				
80	**21.23**	2.95	**19.12**	4.02	**11.81**	4.75						
160	**19.70**	7.31	**11.99**	3.26	**5.02**	1.45						
320	**14.29**	4.81	**6.04**	3.72								
640	**9.75**	1.96										

Figure B.4 Phase 2 measurement tables: Inception 1080p

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