國 立 交 通 大 學

電信工程學系碩士班

碩士論文

# 變動通道暨限時條件下之排程器

# Delay Constrained Scheduling over Fading Channels

研 究 生：林舜華

指導教授：蘇育德博士

中 華 民 國 一 百 零 一 年 十 月

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研 究 生：林舜華 Student : Shun-Hua Lin

指導教授：蘇育德博士 Advisor : Dr. Yu T. Su

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# 變動通道暨限時條件下之排程器

學生:林舜華　　　　　　　　　　　　指導教授:蘇育德　博士

國立交通大學電信工程學系碩士班

## 摘　　要

由於大多數的傳送端裝置都是以電池提供能量,因此提升能量使用效率可以同時提升成本效益與延長電池使用壽命。因為通道會隨著時間以及使用者的位置不同而變化，傳送端可以利用這些變化所造成的分集(diversity)，視不同時間之通道增益適當地調整其傳輸能量，進而大大的提高其能量的使用效率。

在本論文中我們將會探討如何在時域上有效地分配傳輸能量以達到總能量消耗最小化。在已知當前通道增益與未來通道的統計特性,但不知未來通道增益資訊的情況之下，我們將設計一排程器既能節省能源又能滿足其服務質量(Quality of Service)，即資料傳輸流量及限時條件。為了探討通道衰減、限時條件與當前通道增益之間的相互影響，我們在此只討論一基本的排程問題，即我們只討論抵達時間間格固定的單一封包，如:VoIP 網路電話，影音串流都是這類型的限時通訊方式,另外,我們沒有考慮中斷機率(Outage probability)的發生。

利用反住水(Inverse Water-Filling)理論，我們可以推導出最佳非因果(non-causal)的排程器，而在只有兩個時段(time slot)的情況下，也可推導出最佳的因果排程器。此外，我們利用動態規劃法(dynamic programming)也可推導出最佳分配法，但在總時段數大於二時沒有封閉式解法(Closed-form)，即無法用基本函數表示。於是我們提出了兩個次最佳排程方案，一個利用了中央極限定理(Central Limit Theorem)，另一個使用了反住水理論。兩個方法皆是由通道意識與延遲意識所組成的線性組合，且模擬結果顯示當傳送量大時，兩的方法皆接近於最佳排程結果。

此外，我們推廣到多使用者的例子。在第一階段我們只有使用者們的通道特性。在限時條件下，使用者們的分配順序並不重要，因此在此階段只需決定該分配多少時段給每個使用者。之後我們將可把問題視為多個獨立的單一使用者、單載波問題。在多個使用者情況下，排程問題可以分成資源分配、通道指定，即傳送方必須利用順序統計法(order statistics)決定該通道應當指派給哪位使用者，並決定該傳送多少能量以達成總能量消耗最小化的目的。

# Delay Constrained Scheduling over Fading Channels

Student : Shun-Hua Lin Advisor : Yu T. Su

Department of Communications Engineering

National Chiao Tung University

## Abstract

For many wireless transmitters, since most devices are battery powered, increased energy efficiency in data transmission provides significant benefits. Higher energy efficiency may result in prolonging the lifetime of the battery. We seek to find an energy-saving scheduler that sends a packet of $R$ bits within a hard delay deadline $K$ over fading channels. The scheduling policies needs to determine the number of bits transmitted in the current time slot with only the knowledge of current channel state information and the channel statistics of the future channel while satisfying the quality of service QOS constraints as the deadline expired in order to minimize the total energy consumption. In this thesis, we will focus on the interaction between fading, hard deadlines, and causal channel information by studying transmission of only a single packet, and thus do not consider random arrivals since there are applications with deterministic packet arrivals, i.e., VoIP or video streaming where packets arrive regularly and each must be received within a short delay window. Although it is more reasonable to consider random arrivals and outage probability that allows few packets missing, to emphasize the relationship between fading, hard deadlines, and causal channel information, we only consider a fundamental scheduling problem that one packet and no outage is allowed.

An optimal non-causal scheduling policy is derived by inverse water-filling (IWF) method and an optimal causal scheduling policy is also derived for total time slots

$K = 2$. We also develop a dynamic programming formulation that leads to an optimal transmission schedule, however, it is hard to express as a closed form when $K > 2$. Thus, we propose two suboptimal scheduler which give simple structure for general problems, and one utilizes central limit theorem (CLT) for approximation while the other is inspired by the IWF method. The policies are composed of a linear combination of channel-awareness term and delay-awareness term. The numerical results show that the proposed policies are nearly optimal when $R$ is large.

In addition, we extend our work to multiple user case. At the first phase, we only have the channel pdfs of users. Since delay constraint specifies only that the rate is achieved in $K$ blocks, the order of which the users are scheduled within the $K$ blocks is not important in this phase, so the scheduling boils down to sorting out the number of blocks being allocated to each user. After deciding the number of blocks allocated to each user, the problem can be treated as independent single-user single-carrier problems with competitions. With multiple users, the scheduling problem is composed of distributing resources, channel assignment that the transmitter requires to decide which user occupies the channel at any given time slot by order statistic method and bit allocation that how many bits should be allocated in order to minimize the total energy consumption of all users.

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# Chapter 1

# Introduction

It has been shown that future wireless communication systems are expected to provide even higher rate multimedia services with more varieties of QoS requirements while the higher of the energy consumption in network is also required that the tradeoff between expended energy and throughput is of prime importance in increasing transmitter efficiency. Thus, the conservation of energy has recently begun to receive attention where energy conservation refers to efforts made to reduce energy consumption, and may result in a financial cost saving to consumers if the energy savings offset any additional costs of implementing an energy efficient technology. For most devices in wireless communication system are battery powered, for example, a battery- powered cellular phone might want to have a call or download a file from the Internet using the minimum amount of energy while satisfying its delay limitation imposed by quality of service (QOS) constraints, in order to extend the battery lifetime.

Based on the assumption that channel state information (CSI) is available at the transmitter for all time, the problem of finding the best transmission power and its corresponding transmission rate at the transmitter for a time varying fading channel was first addressed in [1] by using very long codewords to capture the ergodic properties of the channel. However, having very long codewords causes excessive transmission delay due to the large interleaver depth. With hard delay constraint, general energy-rate relationships are studied in [2]-[6], but the scheduler has full information of channel state for all time and packet arrival time.

In this thesis, we will focus on the interaction between fading, hard deadlines (which means the data must be transmitted before its expiry.), and causal channel information by studying transmission of only a single packet, and thus do not consider random arrivals since there are applications with deterministic packet arrivals, i.e., VoIP or video streaming where packets arrive regularly and each must be received within a short delay window. [7]-[9] have considered this problem. [7] provides numerical methods for the general case where data throughput is concave in expended energy and the closed form of optimal policies for the special cases where throughput is a piecewise linear function of expended energy in a low signal-to-noise ratio or high bandwidth environment. [8] develops a finite horizon dynamic programming formulation, where the tradeoff between the cost of power and the probability of meeting the quality of service (QoS) constraint and the optimal policy is to save energy by stopping data transmission and waiting for upcoming channel condition improvements. In [9], a random arrival constraint is also considered. This paper allocates power based on the relative value of power weighted against the demanded QOS. The benefit of using this dynamic approach is that it will stop the transmission in poor conditions, as it is predicted that achieving the demanded QOS is expensive in terms of power. On the other hand, with a strict constraint on QOS will force the transmitter to transmit, and it will be an excessive cost in terms of power.

Delay constraint can be described as the probability of the outage event, and related works can be found in [10]-[14]. In [10], it exploits the causal CSI to optimize the power allocation over the blocks for minimizing the outage probability using a dynamic programming approach. Similar in [11] in two-user downlink channel for expected capacity maximization with a short-term power constraint given the causal CSI. In [13] an algorithm that adapts the power allocation over the blocks to minimize the average transmit power while constraining an upper bound of the outage probability constraint was proposed. [14] proposes a suboptimal solution which utilizes the Gaussian approximation on the unknown channels by limit central theorem and simplifies the problem to convex optimization.

We present energy-efficient scheduling policies that reduce the energy consumption of networks while satisfying the hard delay constraint and QOS constraints. In chapter 2, an optimal non-causal scheduling policy is derived by inverse water-filling (IWF) method and an optimal causal scheduling policy is also derived for total time slots $K = 2$. We also develop a dynamic programming formulation that leads to an optimal transmission schedule, however, it is hard to express as a closed form when $K > 2$ as in [15]. Thus, we propose two suboptimal scheduler which give simple structure for general problems, and one utilizes central limit theorem (CLT) for approximation while the other is inspired by the IWF method. The policies are composed of a linear combination of channel-awareness term and delay-awareness term. The numerical results show that the proposed policies are nearly optimal when R is large. In chapter 3, we apply our algorithm to the multi-carrier case. In chapter 4, we extend our work to multiple user case. At the first phase, we only have the channel pdfs of users. Since delay constraint specifies only that the rate is achieved in K blocks, the order of which the users are scheduled within the K blocks is not important in this phase, so the scheduling boils down to sorting out the number of blocks being allocated to each user. After deciding the number of blocks allocated to each user, the problem can be treated as independent single-user single-carrier problems with competitions. With multiple users, the scheduling problem is composed of distributing resources, channel assignment that the transmitter requires to decide which user occupies the channel at any given time slot by order statistic method and bit allocation that how many bits should be allocated in order to minimize the total energy consumption of all users.

# Chapter 2

# Delay Constraint Scheduling for Single User over Fading Channels

## 2.1 Background

Fostered by the remarkable growing of consumer demand for various multimedia applications, increase the efficiency of data transmission has been the significant issue over the past few years. While the most devices are battery powered, the efforts focus on increasing the energy efficiency rather than the data throughput. For example, a battery-powered cellular phone might want to have a call or download a file from the Internet using the minimum amount of energy while satisfying its delay limitation imposed by quality of service (QOS) constraints, in order to extend the battery lifetime.

For delay-sensitive communications, the data must be transmitted before its expiry. Besides, the delay constraint can be considered in terms of whether a required rate is reached within a finite number of time slots or can be described as the probability of the outage event. Thus, for delay-sensitive applications, the target rate is usually given, and the aim problem would be to minimize the transmission energy cost for a given deadline constraint.

Since time-varying channel is the fundamental feature of the wireless communication environment, the transmitter is preferred to transmit higher rate when the channel is in good condition, and transmit less rate when the channel is in bad state. In our design of scheduling strategies, we aim to transmit more data in good quality channel in order to minimize the overall energy consumption while satisfying the user's delay and other quality of service constraints in a time-varying channel.

In this research, we will focus on the interaction between fading, hard deadlines, and causal channel information by studying transmission of only a single packet, and thus do not consider random arrivals since there are applications with deterministic packet arrivals, i.e., VoIP or video streaming where packets arrive regularly and each must be received within a short delay window. Although it is more reasonable to consider random arrivals and outage probability that allows few packets missing, to emphasize the relationship between fading, hard deadlines, and causal channel information, we only consider one packet and no outage is allowed.

## 2.2 System Model

Consider a single-user and single-carrier problem that sends a packet of $R$ bits within $K$ time slots (or blocks as well), which $K$ is referred to as delay deadline, through a flat fading channel as illustrated in Fig. 2.1. We assume that the packet must be

Figure 2.1: single-user delay constraint scheduling.

transmitted by the deadline and no other packet is scheduled in $K$ time slots. Although in realistic traffic, other packets can arrive before the deadline of the previous packet and it is possible to drop some packets, i.e. outage probability is allowed, we simplify the problem and focus on the issue of meeting deadline.

We also assume a time-varying block-fading channel, which fades identically and independently from one block to another, but the fade is considered static within a time slot. The transmitter is assumed to have causal knowledge of the channel state information (CSI), that is, the transmitter only knows the channel state in current time slot and the statistics of the future channes, but the precise future channel states are unknown.

We use $g_k$ to denote the channel gain in $k$th time slot, where $k$ is in descending order, i.e., $k = K$ is the initial slot, $k = K - 1$ is the 2nd slot,..., and $k = 1$ is the final time slot that all remaining bits must be transmitted even if the channel condition is quite poor, and $k$ represents the number of remaining time slots. The channel amplitude can be decomposed into the distance-dependent and the distance-independent terms. For example, when we assume that the channel amplitude, $\sqrt{g_k}$, is rayleigh fading distributed, $g_k$ will be exponential distributed with probability density function (pdf) as following:

$$f(g_k) = \begin{cases} \frac{1}{C_0 d^{-\gamma}} e^{-\frac{g_k}{C_0 d^{-\gamma}}}, & g_k \geq 0; \\ 0, & g_k < 0. \end{cases} \tag{2.1}$$

where mean $E[g_k] = C_0 d^{-\gamma}$ $\forall k$ in which $d$ denotes the distance between the transmitter and the receiver, $\gamma$ is the power loss exponent, and $C_0$ is the distance-independent mean channel power gain.

Based on Shannon-Hartley theorem, the channel capacity $R = log_2(1 + gQ)$, where $g$ and $Q$ denote the channel power gain and energy, and after manipulations, $Q = \frac{2^R - 1}{g}$. Since the future CSI is unknown, the average future energy $\mathbb{E}[Q] = (2^R - 1)\mathbb{E}[\frac{1}{g}]$, and the policy is meaningful only when $\mathbb{E}[\frac{1}{g}]$ is finite. This rules out Rayleigh fading where $g$ is exponentially distributed and thus $\mathbb{E}[\frac{1}{g}]$ is not finite. It means that the scheduler will not accept the users whose channel conditions are not qualified. Therefore, the following are the channel models which $\mathbb{E}[\frac{1}{g}]$ is proved finite:

- Truncated Rayleigh fading

The channel power gain $g$ is truncated exponentially distributed. The truncated exponential distribution restrict the domain from the value which lie below a threshold $\eta$, thus, the channel state $g$ is distributed as following:

$$f(g_k) = \begin{cases} \frac{1}{C_0 d^{-\gamma}} e^{-\frac{g_k-\eta}{C_0 d^{-\gamma}}}, & g_k \geq \eta; \\ 0, & g_k < \eta. \end{cases} \tag{2.2}$$

- Nakagami-m distribution

  Given a shape parameter $\mu$ and a second parameter controlling spread $\omega$, its probability density function (pdf) is:

$$f(x;\mu,\omega) = \frac{2\mu^\mu x^{2\mu-1}}{\Gamma(\mu)\omega^\mu} \exp(-\frac{\mu}{\omega}x^2) \tag{2.3}$$

where $\Gamma(\cdot)$ is the Gamma distribution.

Furthermore, we can prove that the channel power gain is chi- square distributed with degrees of freedom $k$, which is the distribution of a sum of the squares of $k$ independent standard normal random variables.

Let the random variable $Y$ be defined by $Y = x^2$, the event $\{Y \leq y\}$ occurs when $\{X^2 \leq y\}$ or equivalently when $\{0 \leq X \leq \sqrt{y}\}$ for $y$ nonnegative. Thus,

$$F_Y(y) = \begin{cases} 0, & y < 0 \\ F_X(\sqrt{y}), & y > 0 \end{cases} \tag{2.4}$$

and differentiating with respect to $y$, we will get the pdf of the channel power gain

$$\begin{aligned} f_Y(y) &= \frac{f_X(\sqrt{y})}{2\sqrt{y}} \\ &= \frac{\mu^\mu y^{\mu-1}}{\Gamma(\mu)\omega^\mu} e^{-\frac{\mu}{\omega}y} \\ &= \frac{y^{\frac{k}{2}-1} e^{-\frac{y}{2}}}{\Gamma(\frac{k}{2}) 2^{\frac{k}{2}}} \end{aligned}$$

where $\mu = \frac{k}{2}$ and $\omega = k$.

## 2.3 Problem Formulation

We consider a single user sending a packet of $R$ bits before the deadline expired. The problem is to find the minimum required energy for a given target rate $R$ in a transmission of $K$-block flat-fading channels. Thus, we are going to determine the energy, or equivalently the number of bits, to be served during each time slot $k$ such that the expected energy is minimized and the bits are served by the deadline $K$ which is illustrated in Fig. 2.2. The objective function can be expressed as:

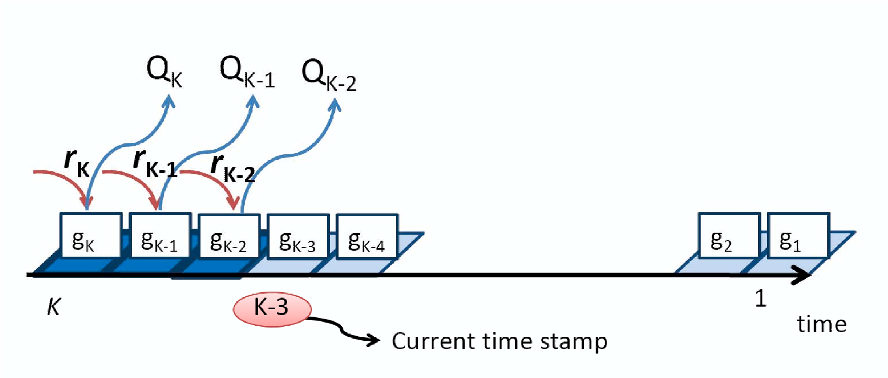


Figure 2.2: single-user scheduling diagram.

$$\min E_k = \min_{r_k} Q_k + \mathbb{E}[Q_r], \qquad \forall k \tag{2.5}$$

subject to

$$Q_k \geq 0, Q_r \geq 0$$

where

$K$ deadline (time slots), $k$ is in descending order and thus represents the number of remaining time slots;

$Q_k$ the energy allocated in $k$th time slot, $Q_k = P_k T$;

$Q_r$ the expected required energy for transmitting the remaining bits, as the time slots are independent and identical distributed(i.i.d), the optimum can always be attained with an equal-power policy, $Q_r = (k-1)TP_r$;

$R$ the total target bits, $\sum_{k=1}^{K} r_k = R$;

$r_k$ the rate achieved at the $k$th block:

$$r_k = \log_2(1 + \frac{Q_k g_k}{N_0}) \text{ in bps/Hz} \tag{2.6}$$

then the energy allocated in $k$th time slot can be expressed as:

$$Q_k = \frac{N_0(2^{r_k} - 1)}{g_k} \tag{2.7}$$

$\tilde{R}_k$ the remaining bits to be sent in the $k$ block;

$g_k$ channel power gain in time slot $k$;

When $r_k$ becomes smaller, the transmission energy in the $k$th time slot is reduced. However, it will leave more bits which need to transmit in the future and the expected energy for transmitting the remaining bits will increase. The optimal energy-efficient scheduler is the set of scheduling functions $\{r_k^{opt}(.,.)\}_{k=1}^{K}$ that minimizes the total expected energy cost:

$$\min_{r_K,\ldots,r_1} \mathbb{E}[\ \sum_{k=1}^{K} Q_k(r_k, g_k)\ ] \tag{2.8}$$

subject to

$$\sum_{k=1}^{K} r_k = R \quad \text{and} \quad 0 \leq r_k \leq \tilde{R}_k \quad \forall k$$

Then, the optimal bit allocation can be formulated sequentially via dynamic programming with the remaining bits $\tilde{R}_k$:

$$r_k^{opt}(\tilde{R}_k, g_k) = \begin{cases} \arg\min_{0 \leq r_k \leq \tilde{R}_k} \{Q_k(r_k, g_k) + \mathbb{E}[\sum_{s=1}^{k-1} Q_r(r_s, g_s)|r_k]\}, & \text{k=K,...,2;} \\ \tilde{R}_1, & \text{k=1.} \end{cases} \tag{2.9}$$

The optimal solution can be found by working backwards in recursive manner. We calculate the optimal scheduling policy at $k = 1$ first, and determine the optimal action at $k = 2$ based on the scheduling policy $r_1$ used at $k = 1$ and so forth. Since the channel power gain $g_k$ is known and future channel state $g_{k-1}, ..., g_1$ are unknown, the current energy cost $Q_k$ is not random but the future energy cost $Q_r$ is random, so we take the expected future energy cost for consideration. If the perfect information of channel state $g$ is available to the transmitter for all time slots, then the optimal solution can be obtained by inverse water-filling procedure, i.e., more power is allocated to the better channel with higher signal-to-noise ratio (SNR), so as to minimize the total energy cost of all blocks. The optimal scheduler with perfect CSI by inverse water-filling method is shown below.

## 2.4 Optimal Scheduling with Perfect CSI by Inverse Water-Filling Method

Here we derive an optimal scheduling policy that the channel state are known non-casually, i.e., $g_K, g_{K-1}, ..., g_1$ are known at $k = K$ by inverse water-filling. The conventional water-filling maximizes the data rate subject to a power constraint, and this is like a dual problem of minimizing the energy cost subject to a rate constraint; thus, it is referred to as inverse water-filling (IWF):

$$\min \sum_{k=1}^{K} \frac{2^{r_k} - 1}{g_k} \tag{2.10}$$

subject to

$$\sum_{k=1}^{K} r_k = R \tag{2.11}$$

$$r_k \geq 0 \tag{2.12}$$

Since it is a convex problem, it can be easily solved by the standard Lagrangian method. Define the Lagrangian as:

$$\Lambda(r_k, \lambda) = \sum_{k=1}^{K} \frac{2^{r_k} - 1}{g_k} - \lambda(\sum_{k=1}^{K} r_k - R) \tag{2.13}$$

where $\lambda$ is a Lagrangian multiplier, and solve:

$$\nabla \Lambda(r_k, \lambda) = 0 \tag{2.14}$$

We get

$$r_k = \log_2(\frac{g_k}{g_{th}}) \tag{2.15}$$

where $g_{th} = \frac{\ln 2}{\lambda}$, and only when $g_k > g_{th}$ , i.e., $r_k > 0$ will the time slot be utilized. Substitute (2.15) into (2.11), and we can get the optimal solution:

$$r_k(\tilde{R}_k, g_k) = \begin{cases} \frac{1}{k'}\tilde{R}_k + \frac{k'-1}{k'}\log_2 \frac{g_k}{\eta_k^{IWF}}, & g_k > g_{th} \\ 0, & g_k < g_{th}. \end{cases} \tag{2.16}$$

where $k' = \sum_{i=1}^{k} 1_{\{g_i > g_{th}\}}$ denotes the number of time slot which is utilized and channel threshold $\eta_k^{IWF} = (\prod_{i=1}^{k-1} g_i^{1_{\{g_k > g_{th}\}}})^{\frac{1}{k'-1}}$. The first additive term corresponds to allocate the remaining bits equally to utilized time slots, and the second term corresponds to decide whether to add/subtract the bits depending on channel state $g$. For $K = 2$, the optimal non-causal scheduling policy is given by:

$$r_2^{IWF}(R, g_2) = \langle \ \frac{R}{2} + \frac{1}{2}\log_2(\frac{g_2}{g_1}) \ \rangle_0^R \tag{2.17}$$

We notice that the optimal non-causal policy determines $r_2^{IWF}$ by inverse water-filling over channel $g_2$ and $g_1$. When $k$=2, more bits will be transmitted if $g_2 > g_1$, on the other hand, less bits will be transmitted if $g_2 < g_1$.

## 2.5 Optimal Causal Scheduling for K=2

First, we consider the special case for $K = 2$ to illustrate the basic idea of the proposed scheduling scheme. Because it is a delay-constraint based transmission, in the final slot ($k = 1$), the scheduler is required to transmit all the remaining bits $\tilde{R}_1$ regardless the channel state $g_1$. At the first time slot $k = 2$, $g_2$ is known but $g_1$ is unknown. Thus, the energy cost in the last time slot is given by $Q_r(\tilde{R}_1, g_1) = \frac{2^{\tilde{R}_1}-1}{g_1}$ for all $g_1$, and the expected cost to serve $\tilde{R}_1$ bits in the final slot is $\mathbb{E}_{g_1}[Q_r(\tilde{R}_1, g_1)] = \mathbb{E}[\frac{1}{g_1}](2^{\tilde{R}_1} - 1)$. The scheduler needs to determine the transmitted bits $r_2$, based on channel state $g_2$ and remaining bits $R$, while balancing the current energy cost and the expected future cost. The objective function can be written as:

$$\begin{aligned}\min E_2 &= \min_{r_2} \quad Q_2 + \mathbb{E}[Q_r] \\ &= \min_{0\leq r_2 \leq R} \quad \frac{1}{g_2}(2^{r_2}-1) + \mathbb{E}[\frac{1}{g_1}](2^{\tilde{R}_1}-1) \\ &= \underbrace{\min_{0\leq r_2 \leq R} \quad \frac{1}{g_2}(2^{r_2}-1) +}_{\text{current energy cost}} + \underbrace{\mathbb{E}[\frac{1}{g_1}](2^{R-r_2}-1)}_{\text{future energy cost}}\end{aligned} \tag{2.18}$$

where taking into account the constraints on $r_2$, the number of transmitted bits can not be less than 0 or more than the total bits $R$.

Since the objective function is convex, we can get the global optimum solution by setting the derivative to zero:

$$r_2^{opt}(R, g_2) = \langle \frac{1}{2}R + \frac{1}{2}\log_2 \frac{g_2}{\eta_1} \rangle_0^R \tag{2.19}$$

where $\eta_1 = \frac{1}{\nu_1} = \frac{1}{\mathbb{E}[1/g_1]}$ is a constant that depends only on the distribution of the channel state $g$ and the operation $\langle . \rangle_a^b$ means that the value is truncated from below at $a$ and truncated from above at $b$.

Like the structure in (2.17), the first additive term in (2.19): $\frac{1}{2}R$ corresponds to allocate equal bits to time slot $k = 1$ and $k = 2$, and the second additive term in (2.19): $\frac{1}{2}\log_2 \frac{g_2}{\eta_1}$ corresponds to a measure of the channel state in first time slot. If the channel quality $g_2$ is bigger than the threshold $\eta_1$, then more bits are allocated than $\frac{1}{2}R$, and if the channel quality $g_2$ is smaller than the threshold $\eta_1$, less bits are allocated to the time slot. Compare the optimal non-causal solution (2.17) with the optimal causal solution (2.19), We notice that the optimal non-causal policy determines $r_2^{IWF}$ by inverse water-filling over channel $g_2$ and $g_1$, while the optimal causal policy determines $r_2^{opt}$ by inverse water-filling over channel $g_2$ and $\frac{1}{\nu_1}(=\eta_1)$ which seems the future channel state as $\frac{1}{\nu_1}$.

Now we discuss further when the number of total time slots $K > 2$. From (2.9), the optimization that the scheduler solves at time slot $k$ is:

$$E_k(\tilde{R}_k, g_k) = \begin{cases} \min_{0\le r_k\le \tilde{R}_k}( \frac{2^{r_k}-1}{g_k} + \bar{E}^{opt}_{k-1}(\tilde{R}_k - r_k) ), & \text{k=K,...,2;} \\ E_1(\tilde{R}_1, g_1), & \text{k=1.} \end{cases} \tag{2.20}$$

where $\bar{E}^{opt}_{k-1}(\tilde{R}_k - r_k) = \mathbb{E}_g[E^{opt}_{k-1}(\tilde{R}_k - r_k, g)]$ denotes the expected cost to serve $\tilde{R}_k - r_k$ bits in $(k-1)$ slots if the optimal allocation policy is used at each time slot. Assuming $\bar{E}^{opt}_{k-1}(\tilde{R}_k - r_k)$ is differentiable, using the same method as in $K = 2$ case, the optimal solution can be obtained by solving (2.21):

$$r^{opt}_k(\tilde{R}_k, g_k) = \begin{cases} 0, & g_k < \frac{\ln 2}{(\bar{E}^{opt}_{k-1})'(\tilde{R}_k)}, \\ \arg_{r_k}\{\frac{2^{r_k}}{g_k} = \frac{1}{\ln 2}(\bar{E}^{opt}_{k-1})'(\tilde{R}_k - r_k)\}, & \frac{\ln 2}{(\bar{E}^{opt}_{k-1})'(\tilde{R}_k)} < g_k < \frac{2^{\tilde{R}_k}\ln 2}{(\bar{E}^{opt}_{k-1})'(0)}, \\ \tilde{R}_k, & g_k > \frac{2^{\tilde{R}_k}\ln 2}{(\bar{E}^{opt}_{k-1})'(0)}. \end{cases} \tag{2.21}$$

When $k = 2$, the future expected energy cost $\bar{E}^{opt}_1(\tilde{R}_1) = \mathbb{E}[\frac{1}{g_1}](2^{\tilde{R}_1}-1)$ and its derivative is in a simple form; thus, the optimal scheduling policy can be solved in closed form as in (2.19). However, it is not that easy to find a closed form for $K > 2$. Since the derivative $(\bar{E}^{opt}_{k-1})'(\tilde{R}_k - r_k)$ is hard to be analytically inverted, the optimal scheduler can not be written in closed form, so the optimal policy can be only expressed by (2.21); thus, it is of interest to develop suboptimal schedulers.

## 2.6 Proposed Scheduling Policies

In this section, we will derive two scheduling equations to determine the number of bits transmitted to each time slot such that the total transmit energy of the system is minimized while the QoS and delay constraints are satisfied.

### 2.6.1 Proposed Scheduling Policy by Central Limit Theorem

First, we would like to introduce the Central limit theorem (CLT) which is mainly used in this algorithm. In probability theory, the Central limit theorem (CLT) asserts that the mean of a sufficiently large number of independent random variables, each with finite mean and variance, will be approximately normally distributed. The law of large numbers states that the arithmetic mean of independent, identically distributed random variables converges to the expected value.

Central limit theorem: Let $X_1, X_2, ...X_n$ be a sequence of independent and identically distributed random variables with expected value $\mu$ and variance $\sigma^2$, which $n$ is a random sample of size. The central limit theorem asserts that for a sufficiently large $n$, the distribution of $S_n = \frac{1}{n}(X_1 + X_2 + ... + X_n)$ will be approximately normal with mean $\mu$ and variance $\frac{\sigma^2}{n}$:

$$\frac{S_n - n\mu}{\sigma\sqrt{n}} \quad \rightarrow \quad N(0,1) \quad as \quad n \rightarrow \infty \tag{2.22}$$

Given the remaining blocks $k$, using CLT we can derive the minimum energy scheduler of single user. First we have to find the formulation of expected future energy cost $\mathbb{E}[Q_r]$, and we will start on the scheduler by the expression of the remaining bits $\tilde{R}_{k-1}$ at time slot $k-1$ which can be written as:

$$\begin{aligned}
\tilde{R}_{k-1} &= \sum_{m=1}^{k-1} r_m \\
&= \sum_{m=1}^{k-1} \log_2(1 + \frac{g_m Q_m}{N_0}) \\
&\approx \sum_{m=1}^{k-1} \log_2(\frac{g_m Q_m}{N_0}) \\
&= \sum_{m=1}^{k-1} \log_2 g_m + \sum_{m=1}^{k-1} \log_2(\frac{Q_m}{N_0})
\end{aligned}$$

Our goal is to minimize the summation of $Q_m$s. First of all, we shall know how to distribute $Q_m$ such that the bit sum is maximized with the condition that $\sum_{m=1}^{k-1} Q_m$ is a constant. By applying Lagrange multiplier, the equal power allocation is optimal. In the equal power allocation strategy,

$$\begin{aligned}\tilde{R}_{k-1} &= \sum_{m=1}^{k-1} \log_2 g_m + \sum_{m=1}^{k-1} \log_2(\frac{Q_m}{N_0}) \\ &= \sum_{m=1}^{k-1} \log_2 g_m + (k-1)\log_2(\frac{Q_r}{(k-1)N_0})\end{aligned}$$

After some manipulations,

$$\begin{aligned}\Rightarrow \log_2(\frac{Q_r}{(k-1)N_0}) &= \frac{\tilde{R}_{k-1}}{k-1} - \frac{1}{k-1}\sum_{m=1}^{k-1} \log_2 g_m \\ \ln(\frac{Q_r}{(k-1)N_0}) &= \frac{\tilde{R}_{k-1}\ln 2}{k-1} - \frac{1}{k-1}\sum_{m=1}^{k-1} \ln g_m \qquad (2.23)\end{aligned}$$

Since the channel gain $\{g_{k-1}, ..., g_1\}$ is a sequence of independent and identically distributed random variables, as sufficiently large $k$, the distribution of $\sum_{m=1}^{k-1} \ln g_m$ can be approximated by central limit theorem (CLT) as normal with

$$\mu_{g_{(k-1)}} = E[\sum_{m=1}^{k-1} \ln g_m] = (k-1)[\ln C_0 - \gamma_{EM}] \quad \text{(truncated exponential)} \qquad (2.24)$$

$$\sigma^2_{g_{(k-1)}} = var[\sum_{m=1}^{k-1} \ln g_m] = \frac{(k-1)\pi^2}{6} \text{(truncated exponential)} \qquad (2.25)$$

where $\gamma_{EM}$ is the Euler-Mascheroni constant. According to (2.23), since the first term of the right hand side is a constant, the right hand side of equation (2.23) is also normal distributed.

Define $X = \frac{Q_r}{(k-1)N_0}$ and $Y = \frac{\tilde{R}_{k-1}\ln 2}{k-1} - \frac{1}{k-1}\sum_{m=1}^{k-1} \ln g_m$, then equation (2.23) can be written as $\ln X = Y$, where

$$\begin{aligned}E[Y] &= \frac{\tilde{R}_{k-1}\ln 2}{k-1} - \frac{1}{k-1}\,\mu_{g_{(k-1)}} \qquad (2.26) \\ var[Y] &= \frac{1}{(k-1)^2}\,\sigma^2_{g_{(k-1)}} \qquad (2.27)\end{aligned}$$

Since Y is normally distributed, X is log-normally distributed which can be expressed as $\ln \mathcal{N}(E[Y], var[Y])$, where

$$\begin{aligned}E[X] &= e^{E[Y]+var[Y]/2} \qquad (2.28) \\ var[X] &= (e^{var[Y]} - 1)e^{2E[Y]+var[Y]} \qquad (2.29)\end{aligned}$$

By using equation (2.28), we can derive the formulation of expected future energy cost as following:

$$E[X] = \frac{E[Q_r]}{(k-1)N_0} = e^{\frac{\tilde{R}_{k-1}\ln 2}{k-1} - [\ln C_0 - \gamma_{EM}] + \frac{\pi^2}{12(k-1)}} \tag{2.30}$$

$$\begin{aligned}
\Rightarrow E[Q_r] &= (k-1)N_0 e^{\frac{\tilde{R}_{k-1}\ln 2}{k-1} - [\ln C_0 - \gamma_{EM}] + \frac{\pi^2}{12(k-1)}} \\
&= (k-1)N_0 e^{-\ln C_0 + \gamma_{EM} + \frac{\pi^2}{12(k-1)} + \frac{(\tilde{R}_k - r_k)\ln 2}{k-1}} \\
&= (k-1)N_0 e^{-\ln C_0 + \gamma_{EM} + \frac{\pi^2}{12(k-1)} + \frac{\tilde{R}_k \ln 2}{k-1}} e^{-\frac{r_k \ln 2}{k-1}} \qquad (2.31)
\end{aligned}$$

Then, the number of bits allocated in time slot $k$ over exponential distributed fading channel can be attained by differentiating (2.7) and (2.31), and set the derivative to 0:

$$\begin{aligned}
\frac{\partial(Q_k + E[Q_r])}{\partial r_k} &= \frac{N_0}{g_k} 2^{r_k} \ln 2 - N_0 \ln 2 e^{-\ln C_0 + \gamma_{EM} + \frac{\pi^2}{12(k-1)} + \frac{\tilde{R}_k \ln 2}{k-1} - \frac{r_k \ln 2}{k-1}} = 0 \\
\Rightarrow r_k &= \langle \frac{1}{k}[\frac{\pi^2}{12\ln 2} + \tilde{R}_k] + \frac{k-1}{k}[\frac{\ln \frac{g_k}{C_0} + \gamma_{EM}}{\ln 2}] \rangle_0^{\tilde{R}_k} \qquad (2.32)
\end{aligned}$$

Compare our bit policy with the optimal scheduling policy (2.21) when $K = 2$. As what we had mentioned before, the additive term $\frac{1}{k}\tilde{R}_k$ in (2.32) denotes allocating equal bits to time slot $\{k, ..., 1\}$, and the term $\frac{k-1}{k} \ln \frac{g_k}{C_0}$ corresponds to the channel state measure in $k$th time slot with a threshold value $C_0$ which depends on the channel statistic and is constant with respect to $k$. Furthermore, we have the addition correction term which depends on channel statistic in our scheduling policy which prevents the scheduler from allocating too few bits to each time slot. We observed that if the scheduler is too passive on scheduling, there will be too many remaining bits left in the last time slot, and this will cause a significant increase on energy cost.

When the deadline is far away (i.e., k is large), the first term in (2.32) is too small to be negligible, and the bit allocation is almost dependent on the instantaneous channel quality which means that only when the channel state is good will the scheduler allocate the bits to the time slot. The scheduler can be more selective because many different channels remain to be seen before the deadline is reached. On the other hand, when

$k$ approaches to 1 (the deadline is coming close), the weight on the channel-dependent term decreases, and the scheduler concerns more on the delay-associated term.

For the purpose of comparing with other previous work, we are going to derive a scheduling policy over the truncated exponential distributed fading channel. Now we are ready to recast the bit allocation policy with $\eta = 0.0000001$. As sufficiently large $k$, the distribution of $\sum_{m=1}^{k-1} \ln g_m$ can be approximated by central limit theorem (CLT) as normal with

$$\mu_{g_{(k-1)}} = E[\sum_{m=1}^{k-1} \ln g_m] = (k-1)(-0.5772) \tag{2.33}$$

$$\sigma^2_{g_{(k-1)}} = var[\sum_{m=1}^{k-1} \ln g_m] = (k-1)(1.6449) \tag{2.34}$$

Let $X = \frac{Q_r}{(k-1)N_0}$ and $Y = \frac{\tilde{R}_k \ln 2}{k-1} - \frac{1}{k-1}\sum_{m=1}^{k-1} \ln g_m$, then equation (2.23) can be written as $\ln X = Y$, where

$$E[Y] = \frac{\tilde{R}_{k-1} \ln 2}{k-1} + 0.5772 \tag{2.35}$$

$$var[Y] = \frac{1.6449}{(k-1)} \tag{2.36}$$

As the method we used before, the expected future energy cost over the truncated exponential fading channel is rewritten as:

$$E[X] = \frac{E[Q_r]}{(k-1)N_0} = e^{\frac{\tilde{R}_{k-1}\ln 2}{k-1} + 0.5772 + \frac{1.6449}{2(k-1)}} \tag{2.37}$$

$$\Rightarrow E[Q_r] = (k-1)N_0 e^{\frac{\tilde{R}_k \ln 2}{k-1} + 0.5772 + \frac{1.6449}{2(k-1)}} e^{\frac{-r_k \ln 2}{k-1}} \tag{2.38}$$

Then, the number of bits allocated in time slot $k$ over truncated exponential distributed fading channel can be attained by differentiating (2.7) and (2.38), and set the derivative to 0:

$$\frac{\partial(Q_k + E[Q_r])}{\partial r_k} = \frac{N_0}{g_k} 2^{r_k} \ln 2 - (N_0 \ln 2) e^{\frac{\tilde{R}_k \ln 2}{k-1} + 0.5772 + \frac{1.6449}{2(k-1)}} e^{\frac{-r_k \ln 2}{k-1}}$$

$$\Rightarrow r_k = \langle \frac{1}{k}[\tilde{R}_k + \frac{0.82245}{\ln 2}] + \frac{k-1}{k}[\frac{\ln g_k + 0.5772}{\ln 2}] \rangle_0^{\tilde{R}_k} \tag{2.39}$$

For the expansion to the multiple user cases, it is needed to find the required time slots before scheduling. Thus, we are attempt to find the optimal required time slot $k^*$ which minimizes the future energy cost in (2.31) when $k = K$ before the scheduling which also fulfills the QOS constraints. For minimizing transmission energy with the condition that the total bits $R$ needed to be transmitted, we can first calculate the number of required time slots $k^*$ by differentiating the expected energy cost $E[Q_r]$ with respect to $k$:

$$\begin{aligned} E[Q_r] &= kN_0 e^{-\ln C_0 + \gamma_{EM} + \frac{\pi^2}{12k} + \frac{R\ln 2}{k}} \\ \frac{\partial E[Q_r]}{\partial k} &= e^{-\ln C_0 + \gamma_{EM} + \frac{\pi^2}{12k} + \frac{R\ln 2}{k}} (1 - \frac{\pi^2}{12k} - \frac{R\ln 2}{k}) = 0 \\ &\Rightarrow 1 - \frac{\pi^2}{12k} - \frac{R\ln 2}{k} = 0 \end{aligned} \tag{2.40}$$

The optimal required time slots can be derived as:

$$k^* = \frac{\pi^2}{12} + R\ln 2 \tag{2.41}$$

where if $k^*$ exceeds the number of total time slots $K$, it would be bounded to $K$, and $k^*$ should be rounded to the nearest integer. Actually, the floor or ceiling operations can be used here, too. After integerizing $k^*$, we will check the expected energy cost with $k^* = \lceil k^* \rceil$ and $k^* = \lfloor k^* \rfloor$, where $\lceil y \rceil$ returns the smallest integer that is bigger than $y$; similarly, $\lfloor y \rfloor$ returns the greatest integer that is smaller than y. If the energy cost with $k = \lceil k^* \rceil$ is smaller than the energy cost with $k^* = \lfloor k^* \rfloor$, then we will set $k^* = \lceil k^* \rceil$ or vice versa. We had compared the result $k^*$ with $k_{best}$, the one obtained by exhausted method that check the energy cost for every $k$, and it turns out that two solutions are the same, $k^* = k_{best}$, shown in fig. 2.3.

However, the conclusion is inaccurate. Although it has good performance on scheduling which will be shown in numerical results, by an intuitive judgement, the more time slots we have, the more flexible constraint we get. Mathematically, the set of optimal $k^*$ is one subset of $K$ such that it shall not outperform than the scheduler with $K$-time-slot constraint.

Figure 2.3: The required time slots $k^*$ we derived is equal to the optimal solution $k_{best}$ found by exhausted search.

### 2.6.2 Proposed Scheduling Inspired by Inverse Water-Filling

In this section, a new proposed algorithm inspired by inverse water-filling is presented. The difficulty to find a general analytic solution to the optimization problem in (2.8) is due to complications caused by the constraint $0 \leq r_k \leq R$ (for each $k$) in the dynamic optimization. Thus, if we relax the constraint while maintaining the other constraint, we can derive the optimal policy in closed form. The problem can be rewritten as follows:

$$\min_{r_K,\ldots,r_1} \mathbb{E}[\ \sum_{i=1}^{K} Q_i(r_i, g_i)\ ] \tag{2.42}$$

subject to

$$\sum_{i=1}^{K} r_i = R$$

By using Lagrange multiplier and differentiate the function with respect to $r_i$,

$$\frac{\partial \sum_{i=1}^{K} Q_i - \lambda(\sum_{i=1}^{K} r_i - R)}{\partial r_i} = \frac{\ln 2 e^{r_i \ln 2}}{g_i} - \lambda = 0 \tag{2.43}$$

$$\Rightarrow r_i = \frac{\ln(\frac{\lambda g_i}{\ln 2})}{\ln 2} \tag{2.44}$$

Substituting the results back into the constraint,

$$R = \sum_{i=1}^{K} r_i = \sum_{i=1}^{K} \frac{\ln(\frac{\lambda g_i}{\ln 2})}{\ln 2} \tag{2.45}$$

$$\begin{aligned} \Rightarrow \ln\lambda &= \frac{R\ln 2 + K\ln\ln 2 - \sum_{i=1}^{K}\ln g_i}{K} \qquad (2.46)\\ r_i &= \frac{\ln\lambda - \ln\ln 2 + \ln g_i}{\ln 2} \\ &= \frac{\frac{R\ln 2}{K} - \frac{1}{k}\sum_{i=1}^{K}\ln g_i + \ln g_i}{\ln 2} \\ &= \frac{R}{K} + \frac{\ln g_i - \frac{1}{K}\sum_{i=1}^{K}\ln g_i}{\ln 2} \\ &= \frac{R}{K} + \frac{\frac{(K-1)}{K}\ln g_i - \frac{1}{K}\sum_{j=1, j\neq i}^{K}\ln g_j}{\ln 2} \end{aligned}$$

Then, we can get the scheduling policy $r_K$ for $k = K$ by taking the expectation on unknown channel gain $\{g_1, ..., g_{K-1}\}$:

$$\begin{aligned} \mathbb{E}[r_K]_{g_1,\ldots,g_{K-1}} &= \frac{R}{K} + \frac{(K-1)\ln(\frac{g_K}{\bar{g}})}{K\ln 2} \\ &= \frac{R}{K} + \frac{K-1}{K}\log_2\frac{g_K}{\bar{g}} \end{aligned}$$

where $\bar{g} = e^{E[\ln g]}$. By truncating the policy at 0 and $\tilde{R}_k$, the general optimal solution for time slot $k$ can be expressed as:

$$r_k = \langle\ \frac{\tilde{R}_k}{k} + \frac{k-1}{k}\log_2\frac{g_k}{\bar{g}}\ \rangle_0^{\tilde{R}_k} \tag{2.47}$$

Observing the equation (2.47), the structure is similar to the optimal solution in (2.17). We can have an insight that our scheduler applies inverse water-filling at every time slot $k$ over the following $k$ channels with channel gain $g_k$ and $(k-1)$ identical channel with channel gain $\bar{g}$ which is illustrated in Fig 2.4.

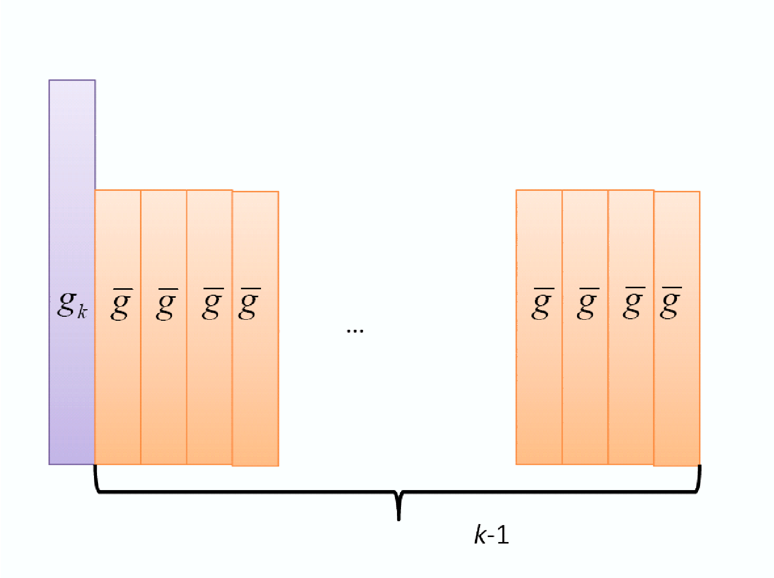


Figure 2.4: Channel gain interpretation for IWF-based algorithm scheme.

Therefore, the expected transmission power of future channels at time slot $k$ is:

$$E[Q_r] = \frac{(k-1)(2^{\tilde{R}_k/(k-1)} - 1)}{\bar{g}} \tag{2.48}$$

Now, differentiate $E[Q_r]$ with respect to $k$ :

$$\frac{\partial E[Q_r]}{\partial k} = \frac{(2^{\tilde{R}_k/k} - 1)}{\bar{g}} - \frac{2^{\tilde{R}_k/k}\tilde{R}_k \ln 2}{k\bar{g}}$$

$$\frac{\partial^2 E[Q_r]}{\partial k^2} = \frac{(2^{\tilde{R}_k/k})\tilde{R}_k^2(\ln 2)^2}{k^3\bar{g}} > 0$$

We can not tell the slope to be positive or negative by the first- order differential equation. However, with the condition that $\lim_{k\to\infty} \frac{\partial E[Q_r]}{\partial k} = 0$, we can say the function $E[Q_r]$ is decreasing as $k$ increasing, which conforms to the fact that the more time slots we use, the less energy to be consumed, see Fig 2.5.

Furthermore, considering the average number of bits transmitted in time slot $k$, we

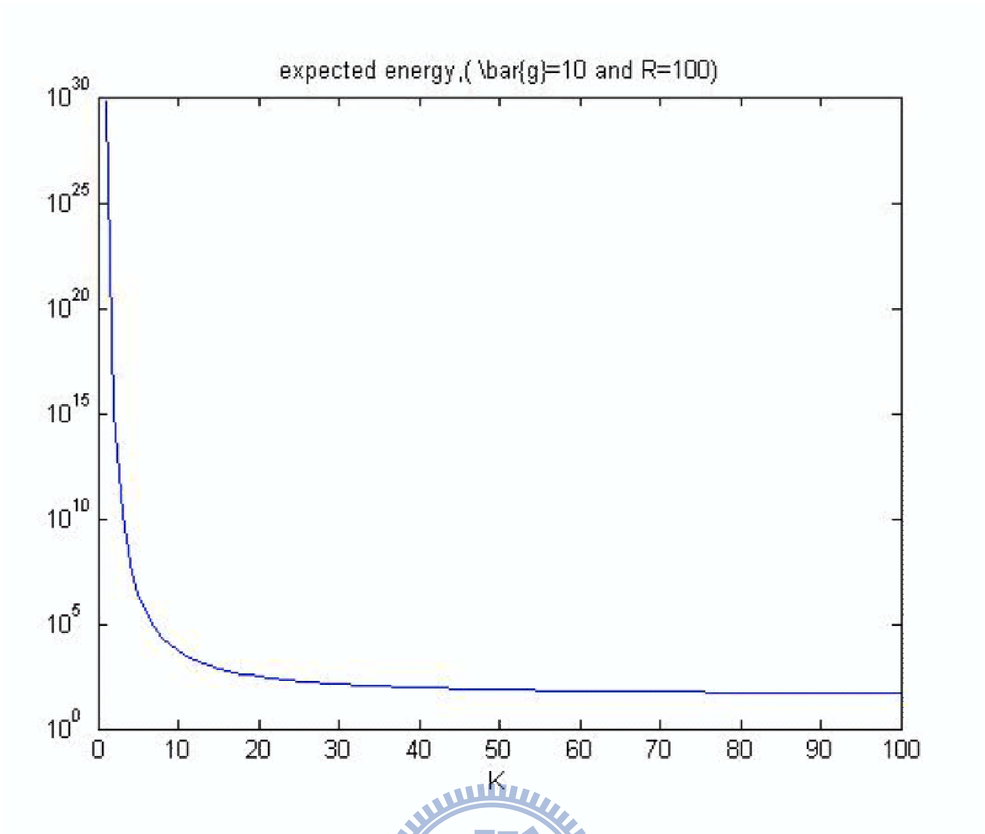


Figure 2.5: The expected energy versus the number of total time slots

can prove our scheduler is unbias that the decision is not aggressive nor conservative.

$$\begin{aligned}\mathbb{E}_{g_k}[r_k] &= E_{g_k}[\frac{\tilde{R}_k}{k} + \frac{k-1}{k}\log_2\frac{g_k}{\bar{g}}] \\ &= \frac{\tilde{R}_k}{k} - \frac{k-1}{k}\log_2\bar{g} + \frac{k-1}{k}E[\log_2(g_k)] \\ &= \frac{\tilde{R}_k}{k} - \frac{k-1}{k}E[\log g] + \frac{k-1}{k}E[\log g_k] \\ &= \frac{\tilde{R}_k}{k}\end{aligned}$$

## 2.7 Numerical Results

First, we will introduce some suboptimal scheduling policies that will be compared with our algorithm in the following.

**A.** *Suboptimal I in [15]*

This paper proposes two suboptimal schedulers that simply apply the inverse water-filling at every time slot $k$. With the intuition of observations described above, the suboptimal I applies this inverse water-filling at every time slot $k$ over the following k channels:

$$g_k, \underbrace{\frac{1}{\nu_1}, ..., \frac{1}{\nu_1}}_{k-1} \tag{2.49}$$

where $\nu_1 = \mathbb{E}[\frac{1}{g_1}]$. Then the bit allocation policy is given by:

$$r_k^{(I)}(\tilde{R}_k, g_k) = \langle \; \frac{1}{k}\tilde{R}_k + \frac{k-1}{k}\log_2 \frac{g_k}{\eta_k^{(I)}} \; \rangle_0^{\tilde{R}_k} \tag{2.50}$$

where $\eta_k^{(I)} = \frac{1}{\nu_1}$ serves as the channel threshold, and is constant with respect to $k$. By using a constant threshold, it shows that Suboptimal I is not selective enough and transmits too many bits when the deadline is far away. To see this, consider the average number of bits transmitted in slot $k$:

$$\mathbb{E}_{g_k}[r_k(\tilde{R}_k, g_k)] = \mathbb{E}_{g_k}[\; \frac{1}{k}\tilde{R}_k + \frac{k-1}{k}\log_2 \frac{g_k}{\eta_k^{(I)}} \;] \tag{2.51}$$

$$= \frac{1}{k}\tilde{R}_k + \frac{k-1}{k}\mathbb{E}[\; \log_2 \frac{g_k}{\eta_k^{(I)}} \;] \tag{2.52}$$

Because $\eta_k^{(I)} = \frac{1}{\nu_1} = \frac{1}{\mathbb{E}[\frac{1}{g_1}]}$, by Jensen's inequality

$$\mathbb{E}[\; \log_2 \frac{g_k}{\eta_k^{(I)}} \;] = \mathbb{E}[\log_2 g_k] + \log_2 \mathbb{E}[\frac{1}{g_1}] > 0 \tag{2.53}$$

Thus, Suboptimal I transmits more than $\frac{R}{K}$ bits on average when scheduling begins, which is in some sense overly aggressive. By contrast, the average number of bits transmitted at time slot $k$ in our algorithm (2.49) shows that our policy has a better performance with no too aggressive or conservative on scheduling.

**B.** *Suboptimal 2 in [15]*

Suboptimal I has a constant threshold which is not selective enough, so it is of interest to have a threshold which varied with k, and it is intuitive to use a larger threshold when the deadline is far away (large $k$), as the scheduler can be more selective because many different channels remain to be seen before the deadline is reached. From [15], the bit allocation policy of suboptimal II is given by:

$$r_k^{(II)} = \langle \frac{1}{k}\tilde{R}_k + \frac{k-1}{k}\log_2 \frac{g_k}{\eta_k^{(II)}} \rangle_0^{\tilde{R}_k} \tag{2.54}$$

where

$$\eta_k^{(II)} = \frac{1}{\mathbb{G}(\nu_{k-1}, \nu_{k-2}, ..., \nu_1)} \tag{2.55}$$

and $\mathbb{G}(\nu_k, ..., \nu_1) = (\prod_{i=1}^{k} \nu_i)^{\frac{1}{k}}$ represents the geometric mean operation, and $\nu_m = (\mathbb{E}[(\frac{1}{g})^{\frac{1}{m}}])^m$, for $m = 1, 2, ....$ The future energy cost of suboptimal 2 in [15] was defined as below:

$$\mathbb{E}[Q_r(\tilde{R}_k)] = k2^{\frac{\tilde{R}_k}{k}}\mathbb{G}(\nu_k, ..., \nu_1) - k\nu_1 \tag{2.56}$$

Compare the two suboptimal policies of [15] with the non-causal optimal solution

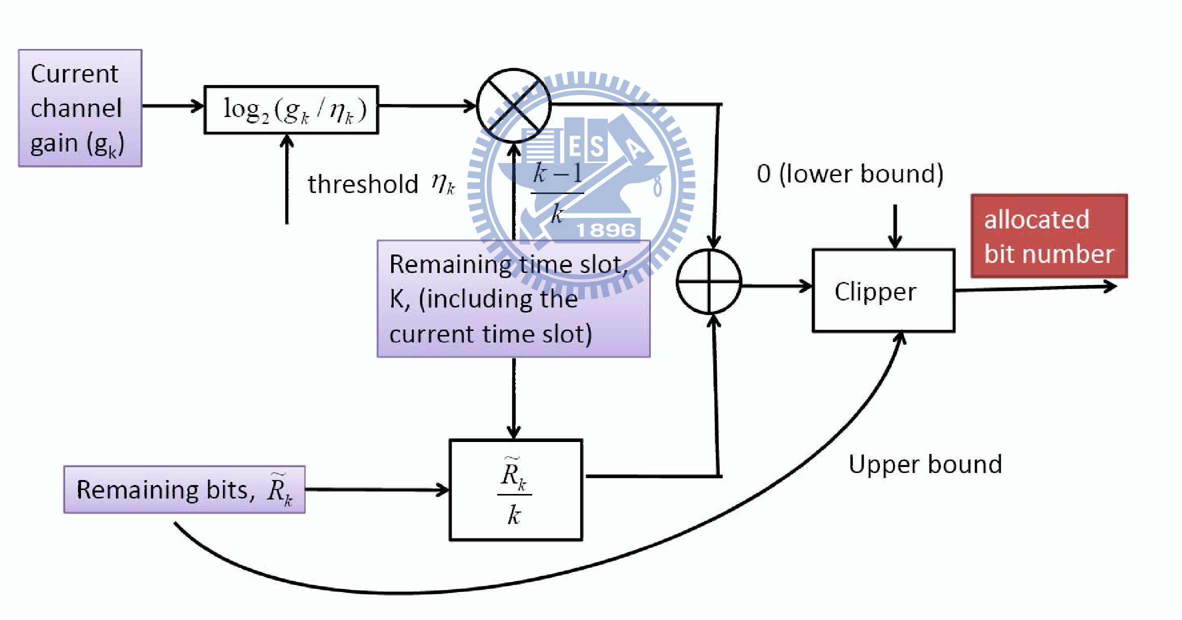


Figure 2.6: General framework of single-user schedulers.

(2.16) and the causal optimal solution derived by IWF (2.47), and we can see that they all have the similar form only with the different channel threshold as in Fig. 2.6:

$$r_k = \langle \frac{1}{k}\tilde{R}_k + \frac{k-1}{k}\log_2(\frac{g_k}{\eta_k}) \rangle_0^{\tilde{R}_k} \tag{2.57}$$

where $\eta_k$ is the channel threshold determined by the individual algorithms. This framework shows how the delay constraint affects the scheduling strategy. At time slot $k$, the scheduler transmits a fraction $\frac{1}{k}$ of the remaining bits $\tilde{R}_k$ plus/minus a quantity depends on the current channel condition. When the channel gain is better than the channel threshold ($g_k > \eta_k$), more bits will be transmitted, while less bits will be served when the channel gain is worse than the channel threshold. For large $k$, the first term is almost negligible, and the scheduler is nearly channel-dependent that it can be aggressive when the channel is in a good condition. On the other hand, for small $k$, we should take more concern on delay deadline, thus, the decision will be more conservative.

**C.** *Equal bit*

The equal bit scheduler is one of the simplest causal scheduler. It serves equal bits on each time slot regardless of the channel gain:

$$r_k^{eq} = \frac{R}{K} = \frac{1}{k}\tilde{R}_k \tag{2.58}$$

### 2.7.1 Numerical results

The simulated performance of the proposed scheduling algorithms are presented in this section. First we evaluate the performance of the proposed scheduling algorithms for the single-user single-carrier scheme over truncated Rayleigh distributed channel in Fig 2.7, and the performance of the proposed scheduling algorithms for the single-user single-carrier scheme over Nakagami distributed channel in Fig 2.8. In Fig. 2.7 and Fig. 2.8 we compare the performance of the proposed algorithms with the suboptimal scheduling policies and optimal non-causal solution. The expected energy for $k = T$ means the average future energy cost we estimated before scheduling, and we observes that it has a significant decrease on total energy consumption via scheduling with the information of the current channel gain.

The CLT-based algorithm and the IWF-based algorithm are superior to suboptimal 1

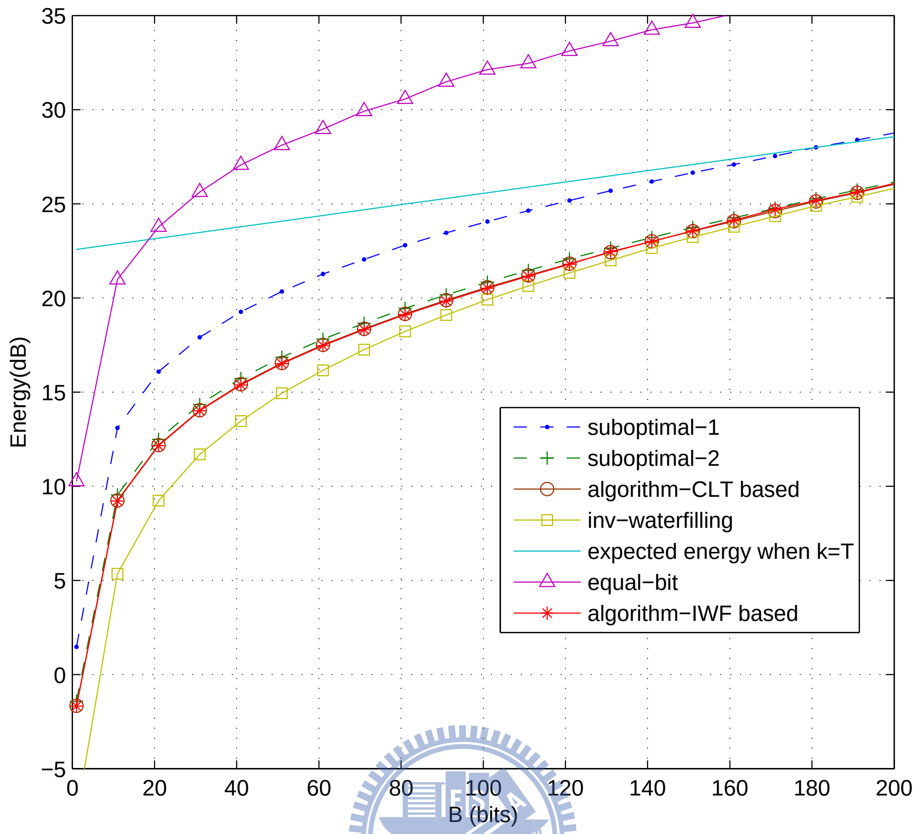


Figure 2.7: Total energy consumption for K=100 over truncated Rayleigh distributed channel.

by a 4 dB margin due to the non-aggressive nature and a slightly superior to suboptimal 2. The difference between our algorithm and suboptimal 2 is not obvious, but our algorithm is possible to be extended to the multiple user cases. Both our algorithms perform nearly as well as the optimal solution when B is large. There are significant differences between equal-bit and other schedulers, which is to be expected given the time diversity available over the time slots.

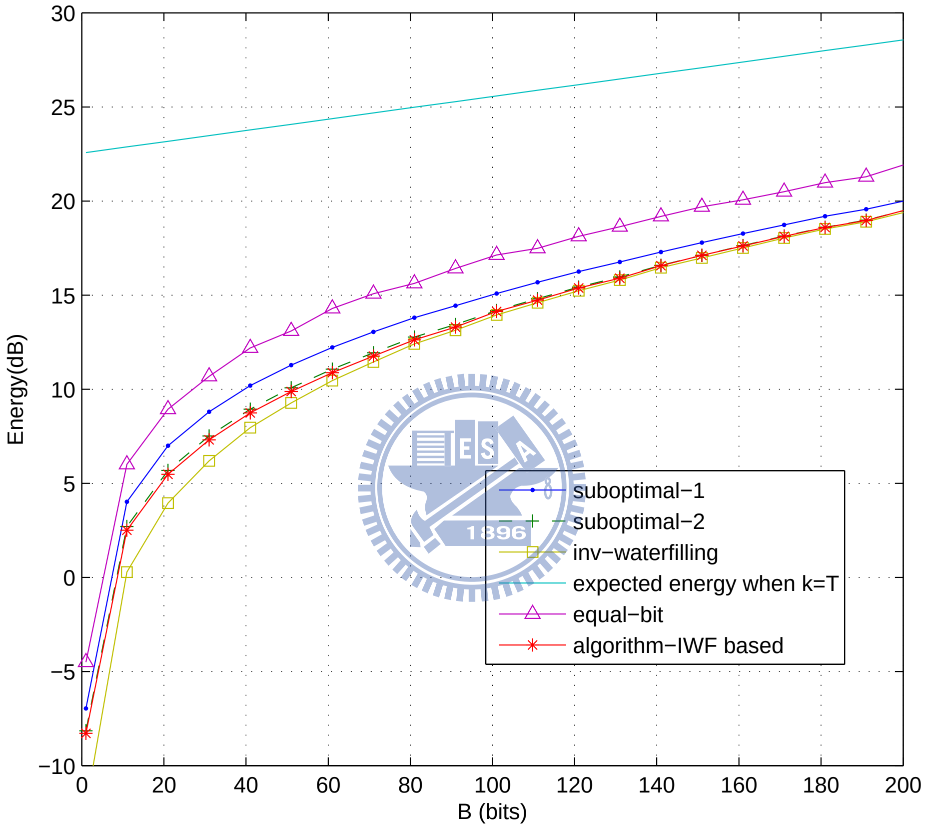


Figure 2.8: Total energy consumption for K=100 over Nakagami distributed channel.

# Chapter 3

# Proposed Single-User Multi-Carrier Scheduler

## 3.1 Scenario

In multi-carrier scenario, we assume that there are $M$ carriers in one time slot. Similar as single-carrier scenario, the scheduler has full CSI of the current $M$ subcarriers and the pdf of future channels only. The packet must be transmitted by the deadline and no other packet is scheduled in $K$ time slots. In this scenario, we try to find out the way which is energy-efficient for allocating bits in each subcarruer.

## 3.2 Proposed Algorithm

If we applied the result of single-carrier case into multi-carrier scenario by assuming that the channel gain of each subcarrier of the future time slot can be viewed as identical and the value is $\bar{g}$ which is illustrated in Fig 3.1. We will obtain exactly the same answer. Inverse water-filling is applied in the case that we have the channel gain of current $M$ subcarriers and $(k-1)M$ identical subcarriers with channel gain $\bar{g}$:

$$g_{1,k}, ..., g_{M,k}, \underbrace{\bar{g}, ..., \bar{g}}_{M(k-1)} \tag{3.1}$$

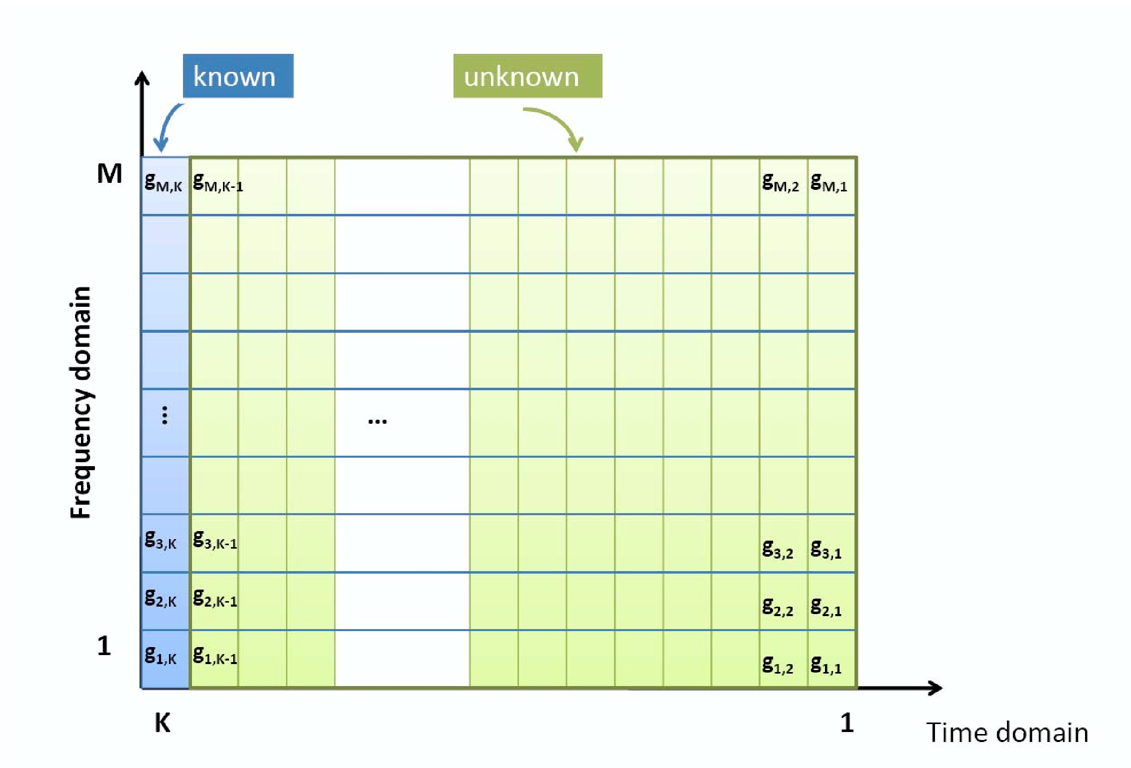


Figure 3.1: Channel gain interpretation for single-user multi-carrier scheme.

where $\bar{g} = e^{E[\ln g]}$. In order to obtain the close form solution to minimize total expected energy, we relax the upper bound and the lower bound of $r_{m,k}$ such that the problem can be written as follows:

$$\min_{r_{1,K},r_{2,K},\ldots,r_{M,K}\cdots,r_{1,1},r_{2,1},\ldots,r_{M,1}} \sum_{m=1}^{M}\sum_{k=1}^{K}\frac{2^{r_{m,k}}-1}{g_{m,k}} \tag{3.2}$$

subject to

$$\sum_{m=1}^{M}\sum_{k=1}^{K} r_{m,k} = R \tag{3.3}$$

By using Lagrange multiplier and differentiate the function with respect to $r_{m,k}$,

$$\frac{\partial}{\partial r_{m,k}}\Big( \sum_{m=1}^{M}\sum_{k=1}^{K}\frac{2^{r_{m,k}}-1}{g_{m,k}} - \lambda\big(\sum_{m=1}^{M}\sum_{k=1}^{K} r_{m,k} - R\big)\ \Big) = 0 \tag{3.4}$$

$$\Rightarrow r_{m,k} = \log_2\Big(\frac{\lambda g_{m,k}}{\ln 2}\Big) \tag{3.5}$$

Substituting the results back into the constraint,

$$\begin{aligned}
\sum_{m=1}^{M}\sum_{k=1}^{K}\log_2(\frac{\lambda g_{m,k}}{\ln 2}) &= R \\
\prod_{m=1}^{M}\prod_{k=1}^{K}\frac{g_{m,k}}{\frac{\ln 2}{\lambda}} &= 2^R \\
\frac{\ln 2}{\lambda} &= (\ \frac{\prod_{m=1}^{M}\prod_{k=1}^{K} g_{m,k}}{2^R}\ )^{\frac{1}{MK}}
\end{aligned}$$

Then, we can get the scheduling policy for subcarrier $m$ at time slot $k$ by taking the expectation on unknown channel gain $\{g_{1,k-1},...,g_{M,k-1},...,g_{1,1},...,g_{M,1}\}$:

$$\begin{aligned}
r_{m,k} &= \mathbb{E}[\ \log_2\frac{g_{m,k}}{(\ \frac{\prod_{m=1}^{M}\prod_{k=1}^{K} g_{m,k}}{2^{\tilde{R}_k}}\ )^{\frac{1}{Mk}}}\ ] \\
&= \log_2\frac{g_{m,k}}{(\ \frac{\bar{g}^{(k-1)M}\prod_{m=1}^{M} g_{m,k}}{2^{\tilde{R}_k}}\ )^{\frac{1}{Mk}}} \\
&= \frac{1}{Mk}\tilde{R}_k + \log_2\frac{g_{m,k}}{(\bar{g}^{(k-1)M}\prod_{m=1}^{M} g_{k,m})^{\frac{1}{Mk}}} \\
&= \frac{1}{Mk}\tilde{R}_k + \log_2\frac{g_{m,k}}{g_{th}}
\end{aligned}$$

where $g_{th} = (\bar{g}^{(k-1)M}\prod_{m=1}^{M} g_{m,k})^{\frac{1}{Mk}}$.

However, there exists one major difference between the result of multi-carrier scenario and the result of single-carrier scenario. When the $r_{m,k}$ is truncated, it implies the $m$th channel of time slot $k$ is unused. This channel shall be removed and we shall perform the inverse water-filling algorithm again without having this channel. Thus the whole procedure is concluded as in Fig 4.1. Note that we can just amendment the $g_{th}$ and total resource number to acquire $r_{m,k}$.

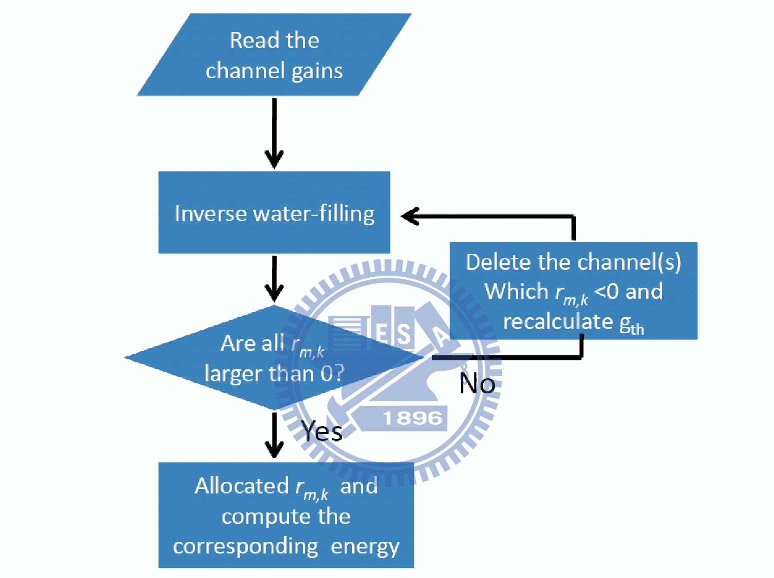


Figure 3.2: Flowchart of the whole procedure for single user case.

# Chapter 4

# Delay Constraint Scheduling for Multiple-user Single-carrier over Fading Channels

## 4.1 System Model

In this chapter, we extend our algorithm to multiple-user cases. Consider a multiple-user single-carrier problem that each user has its own target data rate $R_u$, and the packet has to be transmitted within deadline $K$ which we assume to be the same for every user for simplification through flat fading channels that we had mentioned before. The scheduler has perfect current channel information of each user and the channel statistic of future channel gain, see Fig 4.1. The scheduling problem is composed of channel assignment that the transmitter requires to decide which user occupies the channel at any given time slot and bit allocation that how many bits should be allocated which we discuss in chapter 2 in order to minimize the total energy consumption of all users.

## 4.2 Problem Formulation

The problem can be formulated as:

$$\min_{\{k_u\}} \sum_{u=1}^{U} W_u Q_u \;=\; \min_{\{k_u\}} \sum_{u=1}^{U} W_u \frac{k_u(2^{\frac{R_u}{k_u}} - 1)}{\bar{g}_u} \tag{4.1}$$

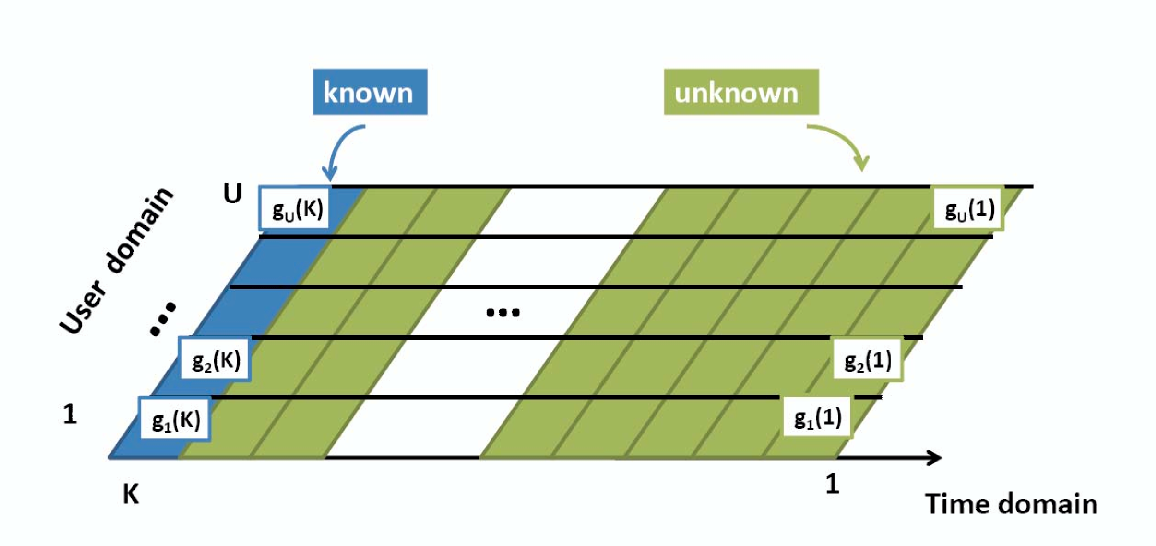


Figure 4.1: Channel gain interpretation for multi-user single-carrier scheme.

subject to

$$\sum_{u=1}^{U} k_u \leq K, \tag{4.2}$$

$$k_u \in \{1, 2, ..., K - U + 1\}, \forall u, \tag{4.3}$$

where

$U$ the total number of users;

$Q_u$ the total energy allocated to user $u$;

$k_u$ the number of blocks allocated to user $u$;

$R_u$ the target data rate of user $u$;

$W_u$ the weighting of user $u$;

Here, we assume we don't have any preference in minimizing energy of the particular users and the weights of users are identical. The user should compete for the resources, because only one user is permitted to gain access to the channel for each resource block. To prevent the case there are users don't own any single resource to transmit, we also enforce and guarantee that each user will obtain at least one resource, but the summation of required time slots of each user can not exceed the delay deadline $K$. However, the number of active users may be larger than the total available resources. The admission control mechanism is needed to prevent the whole system being overwhelmed. To fucus on the main issue, the design of the admission control is out of scope and we assume the number of active users are far less than the number of total resources.

The whole procedure can be decomposed into two phases. At the first phase, the $K$ resources will be distributed among all users. After distributing the $K$ resources to each user, the scheduler decides which user occupies the channel at any given time (or block) based on the current channel condition and then performs the bit allocation. At the first phase, we only have the channel pdfs of users. Since delay constraint specifies only that the rate is achieved in $K$ blocks, the order of which the users are scheduled within the $K$ blocks is not important in this phase, so the scheduling boils down to sorting out the number of blocks being allocated to each user. After deciding the number of blocks allocated to each user, the problem can be treated as independent single-user single-carrier problems with competitions.

## 4.3 Distribute Resources (Phase I)

Recall that the expected transmission energy is a concave function of its occupied resource.

$$\frac{\partial^2 E[Q_r]}{\partial k^2} = \frac{(2^{\tilde{R}_k/k})\tilde{R}_k^2(\ln 2)^2}{k^3\bar{g}} > 0$$

Therefore, when determining the number of blocks allocated to each user based on the channel statistics, we will encounter the NP-hard problem that we want to minimizing the concave objective function with the affine constraint. To solving this troublesome, we propose two algorithm. One is bisection algorithm and the other is greedy algorithm.

### 4.3.1 Bisection Algorithm

Before introducing Karush-Kuhn-Tucker (KKT) condition, the constraint (4.3) is relaxed from integers to positive values. Then differentiate the Lagrange function with respect to $k_u$, and we can get the number of required time slots for each user:

$$\frac{\partial}{\partial k_u}\{\sum_{u=1}^{U}\frac{k_u(2^{\frac{R_u}{k_u}}-1)}{\bar{g}_u}-\lambda(\sum_{u=1}^{U}k_u-K)\}=0 \tag{4.4}$$

$$\Rightarrow \exp^{\frac{R_u\ln 2}{k_u}-1}(\frac{R_u\ln 2}{k_u}-1)=\exp^{-1}(-1-\bar{g}_u\lambda) \tag{4.5}$$

It can be clearly seen that $k_u$ is a function of $\lambda$. If we have $\lambda$, the equation (4.5) called Lambert W function can be helpful to find the one to one connect between $\lambda$ and $k_u$. However, we don't have any information about what $\lambda$ should be. Lambert W function is the inverse function of the function $f(x) = xe^x$. Therefore, we can obtain the formulation of $k_u$:

$$\Rightarrow f^{-1}(\exp^{-1}(-1-\bar{g}_u\lambda))=\frac{R_u\ln 2}{k_u}-1$$

$$k_u=\frac{R_u\ln 2}{f^{-1}(e^{-1}(-1-\bar{g}_u\lambda))+1} \tag{4.6}$$

Before introducing bisection algorithm, we can conclude one important property that when the channel statistics of the users are identical, the optimal $k_u$ can be expressed as:

$$k_u^*=\frac{KR_u}{\sum_u R_u} \tag{4.7}$$

It implies that the required subcarriers are proportional to the required data rates.

The bisection method in mathematics, is a root-finding method which repeatedly bisects an interval then selects a subinterval in which a root must lie for further processing. It is a very simple and robust method, and it converges. First of all, we assume that the problem is feasible, and start with an interval $[\lambda_{min};\lambda_{max}]$ known to contain the optimal value $\lambda^*$. Note that when $\lambda=\lambda_{max}$, $\sum_u K_u(\lambda)<K$.On the other hand,

when $\lambda = \lambda_{min}$, $\sum_u K_u(\lambda) > K$. We then solve the feasibility problem at its midpoint $\lambda_{middle} = (\lambda_{max} + \lambda_{min})/2$, to determine whether the optimal value is in the lower or upper half of the interval, and update the interval accordingly. This produces a new interval, which also contains the optimal value, but has half the width of the initial interval. This is repeated until the width of the interval is small enough.

| | |
|---|---|
| **Step 1**: | (initialization) Given $\sum K_u(\lambda_{max}) < K$, $\sum K_u(\lambda_{min}) > K$, and tolerance $\varepsilon > 0$ |
| **repeat** | |
| **Step 2**: | $\lambda_{middle} = (\lambda_{max} + \lambda_{min})/2$. |
| **Step 3**: | Compute $\sum_u K_u(\lambda_{middle})$ |
| **Step 4**: | If $\sum_u K_u(\lambda_{middle}) < K$, $\lambda_{max} = \lambda_{middle}$. else, $\lambda_{min} = \lambda_{middle}$ |
| **until** | $\lvert \sum_u K_u(\lambda_{middle}) - K \rvert < \varepsilon$. |

Table 4.1: Bisection method.

After bisection algorithm, the $K_u$s may not be integers. Therefore we take floor operation and make $K_u$s be integers. However, the summation of $K_u$ may be less than $K$. In that case, we will reassign the resources to help the most desired users by greedy algorithm. The more detail can be found in the following subsection.

### 4.3.2 Greedy Algorithm

Since our objective is to find the minimum total energy consumption, we are inclined to assign channel to the user who reduces the energy most by the computation of the energy reduction metrics:

$$\Delta Q_u = Q_{u,k_u} - Q_{u,k_u+1}, \quad \forall u \tag{4.8}$$

The one who has the maximum energy reduction while being assigned an additional resource will get one more resource, and keep repeating this procedure till all the resources have be distributed.

| | |
|---|---|
| **Step 1**: | (initialization) $\sum_{u=1}^{U} k_u < K$ |
| **repeat** | |
| **Step 2**: | Compute the power reduction metrics $\Delta Q_u = Q_{u,k_u} - Q_{u,k_u+1}, \quad \forall u$ |
| **Step 3**: | Find $u^* = arg\max_u \Delta Q_u$ and update $k_{u^*} := k_{u^*} + 1$ |
| **until** | $\sum_{u=1}^{U} k_u = K$. |

Table 4.2: Greedy Algorithm.

## 4.4 Channel Assignment and Bit Allocation

After calculating the required time slot of each user, we can start scheduling for each user with the total time slot $K = k_u$. We propose three approaches to schedule.

**I.** The order is predefined and it is independent on the current channel gain.

**II.** The user who have the largest channel gain can occupy this resource if $k_u > 0$ and $k_u$ is updated as $k_u - 1$

**III.** The channel assignment is dependent on $k_u$, $K$, and current channel gain.

In approach I, since the number of time slots which user can use for transmitting decreases, according to the scheduling policy (2.32), the scheduler may be too aggressive to send too many bits in each time slot, and this will cause the scheduler finish transmitting too soon and waste some resources. It will cause the overall transmission energy increases dramatically. Moreover, the approach ignores the user-diversity and does not efficiently use the information of the current channel gain. Thus, apply the scheduling policy in (2.32) directly is not a good idea that it will lose the chance to enhance the overall performance by allocating the channel to the appropriate user who has good channel gain in the current time slot.

In the second approach, the scheduler assigns the time slot to the user based on its channel gain only. We know that the channel gain will be distance-dependent. The user who is close to the receiver will have better channel statistics than other users do. It implies the channel gain of the particular user will be the largest with higher likelihood. We shall point out the issue that its channel gain is larger than others but we will force the user to take the resource without considering this channel which is extremely bad from its perspective. The user-diversity is almost wasted because the channel assignment is highly correlated to the user distances.

To deal with the above issues, approach III does take channel gains, channel statistics, user quotas and total remaining time slots into consideration. Instead of comparing the channel gain directly, we use the order statistic to help us find out which user is most suitable for the time slot. Before going to details, order statistic is briefly introduced.

Order Statistic: Without loss of generosity, there are $n$ identical independent random variables, $X_1, X_2, \ldots, X_n$, and the order statistics $Y_1, Y_2, \ldots, Y_n$ are also random variables, defined by sorting the values of $X_1, X_2, \ldots, X_n$ in decreasing order as in fig 4.2. The first order statistic (or largest order statistic) is always the maximum of the sample, that is,

$$Y_1 = \max\{\, X_1, \ldots, X_n \,\} \tag{4.9}$$

Similarly, the $n$th order statistic (or smallest order statistic) is the minimum, that is,

$$Y_n = \min\{\, X_1, \ldots, X_n \,\} \tag{4.10}$$

Moreover, the cdf of $Y_k$ can be expressed as

Figure 4.2: Probability distributions for 5 order statistic of exponential distribution.

$$
\begin{aligned}
F_{Y_k}(x) &= Pr\{\text{at least } (n-k) \text{ of } X_i \text{ are less than or equal to } x\} \qquad (4.11) \\
&= Pr\{Y_k \geq x\} \\
&= 1 - Pr\{Y_k < x\} \\
&= 1 - \sum_{i=n-k}^{n} C_i^n F^i(x)[1-F(x)]^{n-i}
\end{aligned}
$$

When the scheduler receives the current channel gains, $g_u(K)$ feedback from users, it will calculate $F_{Y_{k_u}}(g_u(K))$ for all users with $n = K$. The reason we choose the $k_u$ as the order is that the user has been assigned with $k_u$ time slots which it can use. It is more reasonable when the user decide whether takes the time slot by consuming its own quotas. Note that when computing $F_{Y_{k_u}}(g_u(K))$, $F_u(x)$ is user-specific.

With the metrics of $F_{Y_{k_u}}(g_u(K))$, the scheduler can decide which user can use this channel by choosing the user with largest $F_{Y_{k_u}}(g_u(K))$. We observe that the larger the order, the larger the probability of the value of $F_{Y_{k_u}}(g_u(K))$ as in Fig 4.3 which means that when having small number of time slots, the channel gain needs to be higher for competition. Once the channel assignment is done, It becomes the single-user single

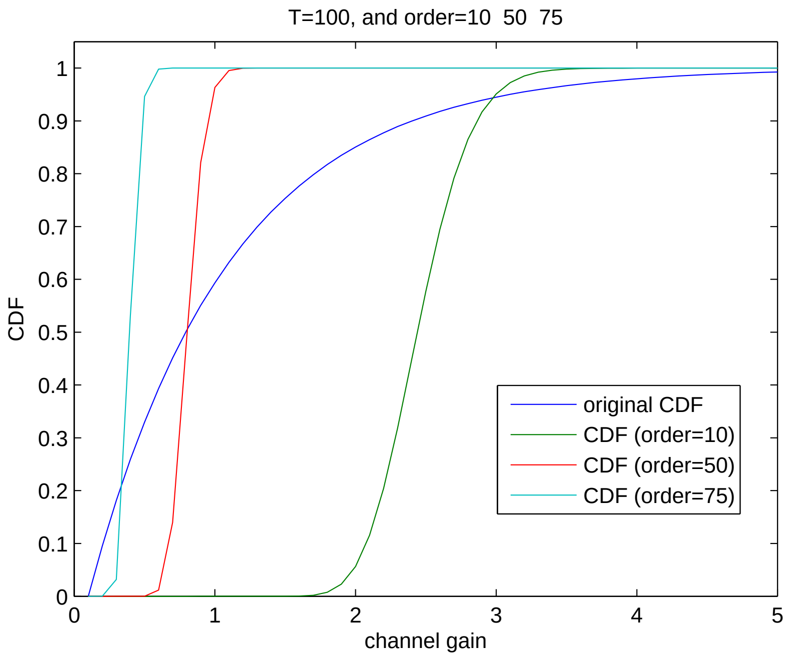


Figure 4.3: CDF versus channel gain for different orders.

carrier scenario and $r_{K_u}$ is

$$r_{K_u} = \frac{R_u}{k_u} + \frac{k_u - 1}{k_u} \log_2 \frac{g_u(K)}{\bar{g}_u} \tag{4.12}$$

The whole procedure including step 1 and step 2 which is concluded as following:

**Step 1**: Distribute the $K$ time slots to all users by bisection or greedy algorithm and obtain $k_u$s.

**Step 2**: **while** $(K >= 1)$

**1.** Compute $F_{Y_{k_u}}(g_u(K))$ based on the current channel gain, $K$, $k_u$s and user-specific channel statistics.

**2.** Find the most suitable user:
$u* = \arg\max_u F_{Y_{k_u}}(g_u(K))$.

**3.** Do bit allocation:
$r_{K_{u^*}} = \frac{R_{u^*}}{k_{u^*}} + \frac{k_{u^*}-1}{k_{u^*}} \log_2 \frac{g_{u^*}(K)}{\bar{g}_{u^*}}$

**4.** Update parameters:
$k_{u^*} = k_{u^*} - 1$, $K = K - 1$ and $R_{u^*} = R_{u^*} - r_{K_{u^*}}$

**end**

Table 4.3: Proposed scheduling Algorithm.

There is one variant that will do step 1 again (redistribute resource) after bit allocation.

| | |
|---|---|
| **Step 1**: | Distribute the $K$ time slots to all users by bisection or greedy algorithm and obtain $k_u$s. |
| **Step 2**: | **while** $(K >= 1)$ |
| | **1.** Compute $F_{Y_{k_u}}(g_u(K))$ based on the current channel gain, $K$, $k_u$s and user-specific channel statistics. |
| | **2.** Find the most suitable user: $u* = \arg\max_u F_{Y_{k_u}}(g_u(K))$. |
| | **3.** Do bit allocation: $r_{K_{u*}} = \frac{R_{u*}}{k_{u*}} + \frac{k_{u*}-1}{k_{u*}} \log_2 \frac{g_{u*}(K)}{\bar{g}_{u*}}$ |
| | **4.** Update parameters: $k_{u^*} = k_{u^*} - 1$, $K = K - 1$ and $R_{u^*} = R_{u^*} - r_{K_{u^*}}$ |
| | **5.** Distribute again the $K$ time slots to all users by bisection or greedy algorithm and obtain $k_u$s. |
| | **end** |

Table 4.4: Proposed scheduling Algorithm 2.

## 4.5 Numerical Results

The performance of the proposed algorithms over truncated Rayleigh distributed channel for multi-user scheme is in fig 4.4 with parameter $\lambda = 1$ and threshold $\eta = 0.0000001$, and Nakagami distributed channel for multi-user scheme is in fig 4.5 with degree of freedom $= 4$. Throughout the simulations, we assume the deadline $K = 100$, the number of user $U = 4$, and the bit allocation algorithm we use here is IWF-based policy in chapter 2.6.2.

In fig 4.4 and 4.5, The proportional fairness algorithm has the worst performance since it takes the balance between fairness and energy consumption in consideration.

If the users have the same target data rate to transmit, it is similar as round robin algorithm that it exchanges energy cost for fairness. We can observe that our algorithm is superior to equal bit algorithm by a 6 dB margin. We also see that no matter what algorithm we user in distribute resource phase, either greedy or KKT condition method will result in same performance and it also has the same results whether we recalculate the number of required time slot in the beginning of every time slot or not. In addition,

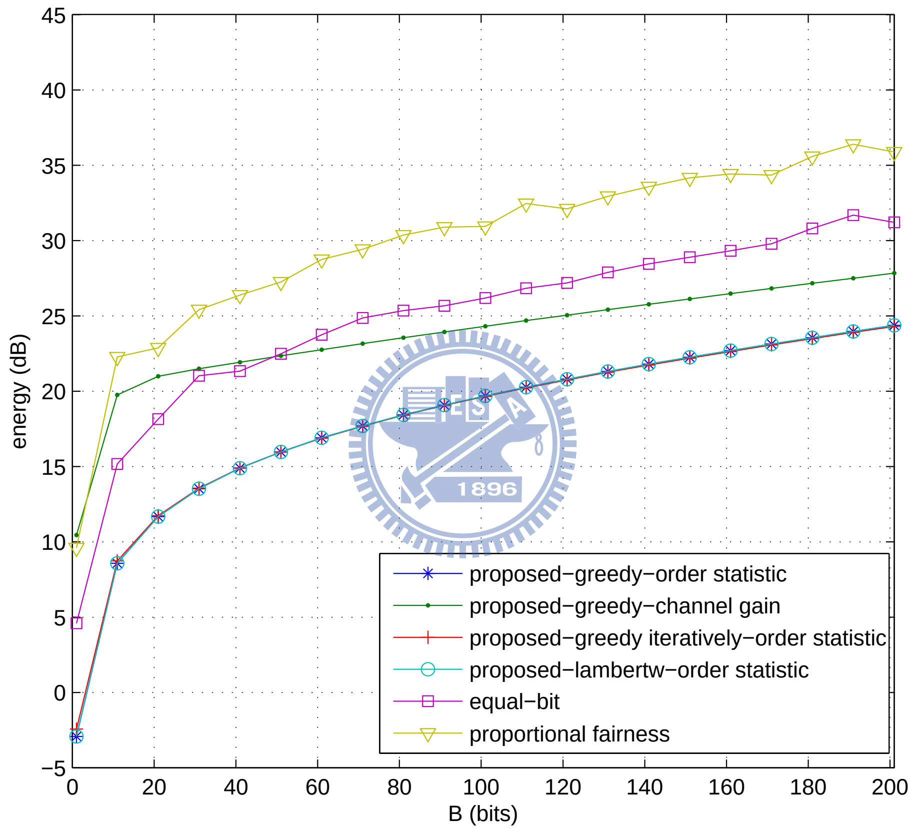


Figure 4.4: Total energy consumption for K=100 over truncated Rayleigh distributed channel for multi-user scheme.

for channel assignment phase our algorithm which assigns channel according to CDF value by order statistic method performs better than the one just considers the channel gain by a 5 dB margin.

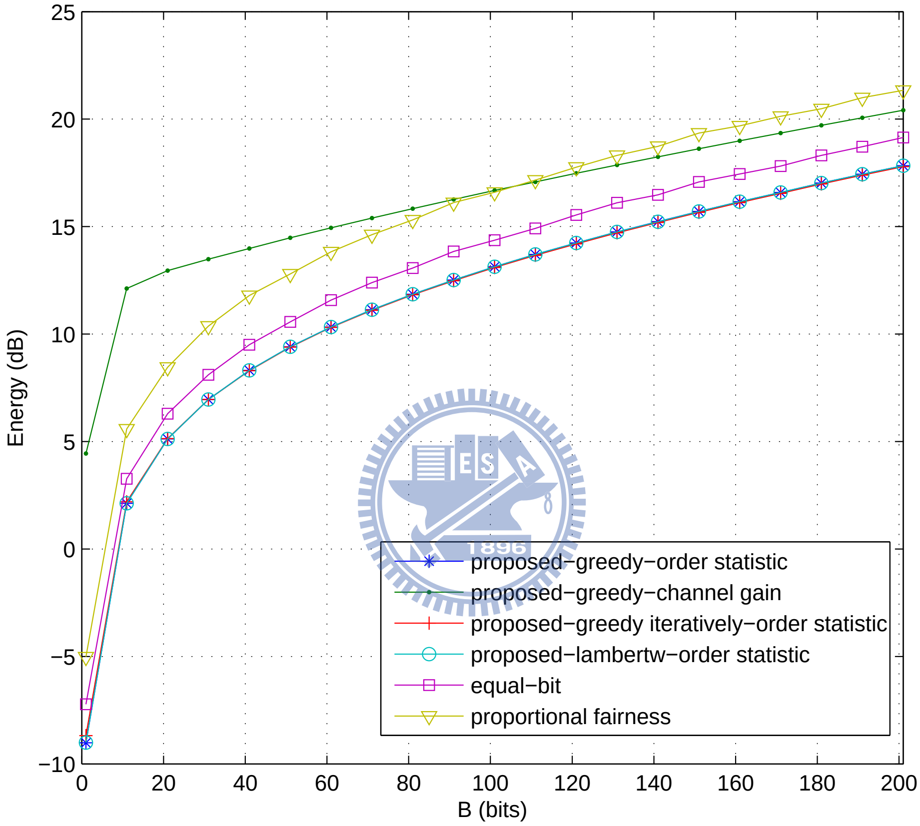


Figure 4.5: Total energy consumption for K=100 over Nakagami distributed channel for multi-user scheme.

# Chapter 5

# Conclusion

Energy-efficient scheduling over fading channels in wireless communication system is critical in minimizing total energy consumption while satisfying the hard delay deadline and QOS constraints in order to extend the battery lifetime. We assume that the information of the current channel state is perfect known and the future channel gain is unknown that we have the channel statistic only while scheduling. In this thesis, we have presented two scheduling policies that minimize the total consumed power while meeting the delay requirements for single user case and both of them have the similar structure with the optimal non-causal solution. Both the proposed schedulers are in simple form and they give insight that the scheduler is channel-dependent when the deadline is faraway (i.e. $K$ is large) while delay-dependent when $K$ is small. We also proved that the proposed IWF based scheduler is unbias which means the decision is not too aggressive or conservative. Observed from the proposed algorithms, the channel gain of the future time slot can be viewed as identical and the value is $\bar{g}$. The simulation results shows that the performance is nearly as well as the optimal non-causal solution when the required transmitted bits is large.

We also consider the scheduling problem for multiple carrier case with the knowledge of channel state information of $M$ subcarriers in the current time slot. The derived scheduler is in closed form but has a difference from the single-user single-carrier scheme that after calculation if the number of the transmitted bit terms out to be negative, we have to discard that channel and reschedule again.

Furthermore, we extend our algorithms to multi-user single-carrier case where the scheduling procedure is composed of two phases: distribute the resources, channel assignment and bit allocation. First we compute the number of required time slots of each user by bisection method, since delay constraint specifies only that the rate is achieved in K blocks with some probability, the order of which the users are scheduled within the K blocks is unimportant, so the scheduling boils down to sorting out the number of blocks being allocated to each user. Thus, the multiple user problem is divided into several independent single user subproblems. Second, we proposed a channel assignment algorithm by order statistic. Taking channel gain, channel statistic, users' quotas and total remaining time slots into consideration, we can find out which user is most suitable for that time slot, and then perform bit allocation.

Finally, our proposed algorithm can be generalized into correlated channel cases easily. In these cases, we apply the conditional probability density function instead of independent channel assumption and we expect this to be more practical and important over wireless networks.

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# Curriculum Vitae

| Personal Data | | | |
|---|---|---|---|
| Name | Chinese: 林舜華<br>English: Shun-Hua Lin | Birthday<br>dd/mmm/yyyy | 22 /09/1986 |
| Present Address | Room 811, Engineering Building 4,No. 1001, Ta-Hsueh Road,<br>Hsin Chu 300, Taiwan, R.O.C. | | |
| Permanent Address | 4F., No.1, Ln. 450, Sec. 5, Chenggong Rd., Neihu Dist., Taipei City 114, Taiwan (R.O.C.) | | |
| E-Mail Address | dulululin@gmail.com | Mobile Phone:<br>0921423809 | |

| Education | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Degree | Name of School | From | | To | | Major Subject | Graduated | |
| | | Y | M | Y | M | | Yes | No |
| Bachelor | National Chiao Tung University | 2005 | 9 | 2009 | 6 | Department of Communication Engineering | V | |
| Master | National Chiao Tung University | 2009 | 9 | present | | Department of Communication Engineering | | |
| Master | École Supérieure d'Électricité (Supélec) | 2011 | 9 | 2012 | 9 | Master SAR (Systèmes Avancés de Radiocommunications) | V | |