SENSITIVITY OF OPPORTUNISTIC SCHEDULERS TO ERRONEOUS RATE FEEDBACK

A Project Report

submitted by

V S KALICHARAN PULLELA

in partial fulfilment of the requirements
for the award of the degree of

MASTER OF TECHNOLOGY

DEPARTMENT OF ELECTRICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY MADRAS.

MAY 2014

REPORT CERTIFICATE

This is to certify that the report titled **SENSITIVITY OF OPPORTUNISTIC SCHEDULERS TO ERRONEOUS RATE FEEDBACK**, submitted by **V S Kalicharan Pullela**, to the Indian Institute of Technology, Madras, for the award of the degree of **Master of Technology**, is a bona fide record of the project work done by him under our supervision. The contents of this report, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

Prof.Venkatesh Ramaiyan
Project Guide
Assistant Professor
Department of Electrical Engineering
IIT-Madras, 600 036

Prof.Sheetal Kalyani
Project Guide
Assistant Professor
Department of Electrical Engineering
IIT-Madras, 600 036

Place: Chennai

Date: 29th May 2014

ACKNOWLEDGEMENTS

I thank my parents for their constant support and motivation. I am grateful to **Dr.Sheetal Kalyani & Dr.Venkatesh Ramaiyan** for their guidance throughout the project. Their valuable insights helped me a lot for the progress of my project. I also thank my friends. I thank my college **IIT Madras** for providing me the infrastructure required for my project.

ABSTRACT

KEYWORDS: Opportunistic schedulers ; Sensitivity analysis; Proportional fairness

In this report, we present our sensitivity analysis of opportunistic schedulers in the presence of erroneous rate feedback. A malicious user reports incorrect channel feedback to an opportunistic base station. We have analyzed the effect of erroneous rate feedback by the malicious user on opportunistic schedulers like max-min fair scheduler, sum-rate maximizing scheduler and proportional fair scheduler. We characterize the loss in airtime due to incorrect rate feedback and also identify the worst-scenario strategy for the malicious user. Using simulations, we evaluate the impact of erroneous rate feedback for a variety of channel and network conditions. We infer that max-min fairness and sum rate maximization are very sensitive to erroneous rate feedback, while, proportional fair scheduler seems robust in terms of isolation.

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CHAPTER 1

Introduction

We study the performance of opportunistic scheduling strategies in cellular wireless networks in the presence of malicious user. We consider single cell and multi cell environments of a cellular wireless network with a base station and a fixed number, N, of wireless users. We assume that the wireless channel is slotted and the channel fades randomly and independently over slots. The base station scheduler is opportunistic and seeks to maximize a known network utility (or a notion of fairness) with channel quality feedback from the wireless users. In this setup, we study the sensitivity of the opportunistic schedulers(OS) in the presence of malicious user.

We assume that a malicious user is capable of reporting incorrect channel quality information (CQI) to the base station with malicious or selfish intent. We, then, aim to analyze the sensitivity of the various popular scheduling strategies to such incorrect feedback. In particular, we study the impact of the incorrect feedback on the air time share, access delay and long term average throughput (of the normal users) as a function of the scheduling strategies.

The latest cellular standards including LTE-A/3GPP (Al-Rawi *et al.* (2008)) seek feedback from the users to enable opportunistic scheduling. In every frame, the rate at which a user is scheduled depends on the feedback received from the user. It is assumed in the implementations that the feedback from the users are reasonably accurate. In the event of incorrect channel feedback, the scheduler may become suboptimal as there is no provision made available in the implementations to identify such cases. We seek to clearly distinguish this case with the scenario where the channel quality information is inaccurate. In the later case, the base station may use adaptive retransmission techniques to mitigate such effects.

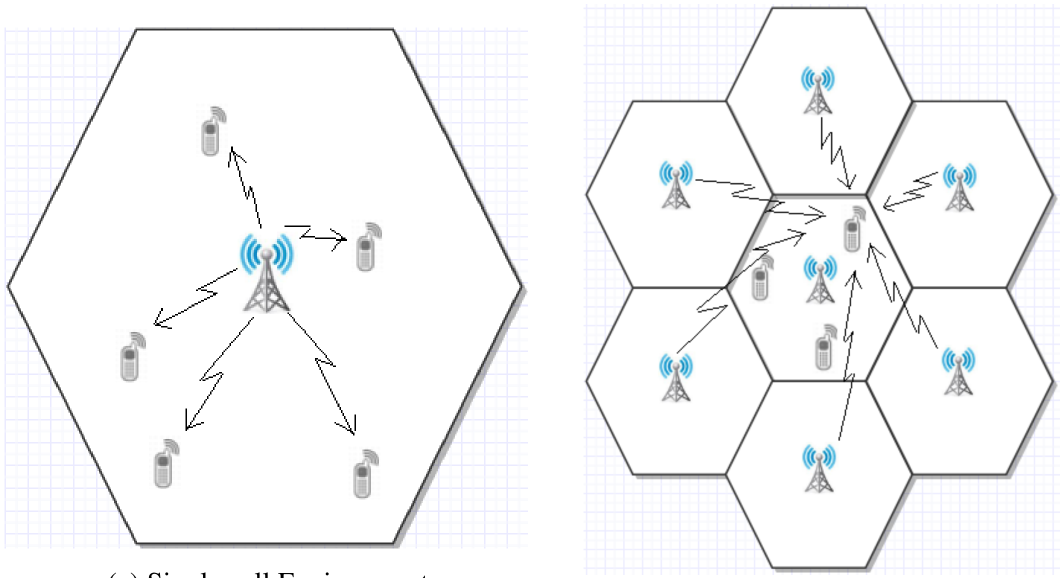
In chapter 2, we describe the network model and assumptions and in chapter 3, we discuss prior literature relevant to our work. In chapter 4, we define different performance metrics. In chapter 5, we study the impact of a single malicious user on the air time share, access delay and long term average throughput of a single normal user.

We show analytically that the air time share of the normal user can be arbitrarily small with incorrect channel feedback. We characterize the worst-case strategy for proportional fairness, max-min fairness and sum-rate maximization schedulers. In chapter 6, we characterize the impact of malicious user for known distributions such as Rayleigh, Ricean and Nakagami fading channels as well as for large N in singel cell and multi cell environments. In chapter 7, we conclude with a discussion on future work.

CHAPTER 2

Network Model and Assumptions

We consider a single cell and multi cell environment of a cellular wireless network with a base station and a fixed number, N, of wireless users. We assume that the wireless channel is slotted with slots of size τ seconds. The users time share the common wireless channel and a single user can be scheduled in a slot. We assume that the base station coordinates the channel access among the wireless users with feedback from the wireless users. We consider both uplink and downlink traffic scenario and we assume that the data queues of the users are saturated, i.e., the users always have data. Figure 2.1a shows in a single environment and figure 2.1b shows multicell interference environment.



(a) Single cell Environment

(b) Multi-cell Environment

Figure 2.1: Cellular Networks Models

2.1 Channel Model

We consider a random fading wireless channel between the base station and the users. We assume that the channel state remains constant in a slot and may vary over time slots. Let $(C_1(t), C_2(t), \cdots, C_N(t))$ model the vector of channel state in slot t, where $C_i(t)$ is the channel state of user i at time t. For example, $C_i(t)$ could represent the channel quality information (CQI), channel gain or the signal to interference plus noise ratio (SINR) in slot t. Let $(R_1, R_2(t), \cdots, R_N(t))$ be the vector of supported maximum rates for the users in slot t, i.e., $R_i(t)$ is the maximum rate supported for user i in the slot t if user i is scheduled. In this work, we consider a single cell and multi cell environment of a cellular wireless network and we schedule a single user in a slot. Hence, In a single cell environment $R_i(t)$ is a function of $C_i(t)$ (and would not depend on $C_j(t)$ where $j \neq i$) and in a multi cell environment $R_i(t)$ is a function of $C_i(t)$,interference from other cells but in both cases it may depend on AMC, radio and other transceiver considerations. For example, $C_i(t)$ can be the Rayleigh channel gain and in a single cell environment, the maximum supported rate in the slot $R_i(t)$ can be $R_i(t) := W \log\left(1 + \frac{C_i^2(t)}{\sigma^2}\right)$ bits per second (where W is the channel bandwidth and σ^2 is the AWGN noise power). In a multicell environment, the maximum supported rate in the slot $R_i(t)$ can be $R_i(t) := W \log\left(1 + \frac{C_i^2(t)}{I(t)+\sigma^2}\right)$ bits per second (where $I(t)$ is interference power, W is the channel bandwidth and σ^2 is the AWGN noise power).

2.2 Scheduler and Notion of Fairness

In this work, we assume that the users feed back channel state information to the base station in every time slot to aid in scheduling. Let $(\hat{R}_1(t), \hat{R}_2(t), \cdots, \hat{R}_N(t))$ be the estimate of the maximum supported rates for the users at the base station at the beginning of every slot t. The base station would now schedule a user based on the reported channel rates and the network objective. For example, the scheduler that maximizes the sum rate schedules

$$\text{argmax}\left(\hat{R}_1(t), \hat{R}_2(t), \cdots, \hat{R}_N(t)\right)$$

and the scheduler that implements proportional fairness schedules

$$\text{argmax}\left(\frac{\hat{R}_1(t)}{\bar{R}_1(t)}, \frac{\hat{R}_2(t)}{\bar{R}_2(t)}, \cdots, \frac{\hat{R}_N(t)}{\bar{R}_N(t)}\right)$$

where, $\bar{R}_i(t) = \frac{1}{t}\sum_{k=1}^{t} I_{\{\text{user } i \text{ is scheduled}\}}(t)\hat{R}_i(t)$, is the time average throughput of user i up to time t (as recorded by the base station).

Let the base station schedule a user i with the reported channel rate $\hat{R}_i(t)$ in slot t. We assume that the data communication of user i at the reported channel rate $\hat{R}_i(t)$ is successful if and only if $\hat{R}_i(t) \leq R_i(t)$. In the event $\hat{R}_i(t) \geq R_i(t)$, the data communication is assumed to have failed and all the data is assumed to be lost. In the event of inaccurate channel feedback, the event $\hat{R}_i(t) \geq R_i(t)$ would trigger adaptive retransmission strategies to mitigate packet and bit errors.

2.3 Malicious User

In this work, we are interested in analyzing the impact of incorrect channel feedback on the network performance. We assume that the malicious user reports incorrect channel values, i.e., $\hat{R}_i(t)$ need not be $R_i(t)$, and seek to study the sensitivity of the various scheduling strategies (proportional fairness, max-min fairness and sum-rate maximization). In the event $\hat{R}_i(t) \geq R_i(t)$, the data communication is assumed to have failed and all the data is assumed to be lost. However, the malicious user may not report a packet error and fake reception with positive acknowledgement. We note that the current implementations permit the possibility of such response and there are no provisions to identify such incorrect channel and data feedback. In such cases, the network performance would be suboptimal and we are interested in characterizing the sensitivity of the network performance to incorrect channel feedback.

2.4 Objective

The base station seeks to implement a notion of fairness using the channel feedback from the wireless users. In this setup, we seek to characterize the robustness of the various schedulers in the presence of a malicious user. In particular, we characterize the impact of incorrect channel feedback on the air time share, access delay and long term average throughput of the normal user for a variety of channel and network scenarios. For example, we now know that proportional fairness is not time fair (Wengerter *et al.* (2005)). Hence, a user may gain undue advantage (in terms of air time share) by reporting an incorrect channel distribution. Our work seeks to identify robust network utilities and notions of fairness for cellular wireless networks.

CHAPTER 3

Related Literature

The rate region of a fading wireless channel and throughput/utility optimal schedulers have been studied in a number of earlier works for a variety of channel and network assumptions. The rate region of a multihop ad hoc wireless network (and a throughput optimal scheduler for the rate region) was first characterized in Tassiulas and Ephremides (1992) and was generalized to fading time-varying channels in Neely *et al.* (2005). Using a stochastic approximation framework, in Kushner and Whiting (2004), Kushner and Whiting studied the convergence of a proportional fair scheduler for a cellular wireless network. A generalized gradient scheduling strategy was proposed in Stolyar (2005) to maximize any concave network utility over the rate region of the wireless channel. In Liu *et al.* (2003), Liu et al propose a general framework for opportunistic scheduling and study optimal strategies for different notions of fairness such as temporal fairness and utilitarian fairness. We note that all the above works had assumed that the channel information is perfectly available at the base station at the beginning of every slot. In our work, we aim to study and characterize the performance of such schedulers with incorrect channel feedback.

In Gopalan *et al.* (2012), Aditya et al study the rate region and optimal schedulers for a wireless network with limited but perfect feedback. A similar model was considered in Manikandan *et al.* (2009) and the rate region was characterized. In Lin and Shroff (2005), the impact of imperfect schedule on the rate region and throughput optimality was studied. It is assumed that the base station has access to perfect channel state information but approximates the schedule only to minimize computation. A feasible rate region under an asynchronous network information model was characterized in Ying and Shakkottai (2011) for a multihop wireless network. The network information in Ying and Shakkottai (2011) is assumed to be delayed and not in error. In our work, we assume that the channel information is incorrect both intentionally and otherwise and we seek to characterize the network performance.

In Kavitha *et al.* (2010), Kavitha et al study parametric α-fair scheduling from a game theoretic perspective in the presence of non cooperative mobiles. In Kong *et al.*

(2008), Kong et al analyzed the impact of selfish behaviors on performance of MR algorithm and using mixed game theoretic model, showed that the Maximum Rate packet scheduling algorithm can lead non-cooperative users to undesirable Nash equilibriums. In Kong *et al.*, Auction based scheduling algorithm is proposed in presence of non-cooperative multiuser OFDM systems. In our work, we assume that the identity of the malicious user may not be known and the users are generally unaware of any design.

CHAPTER 4

Performance Metrics

4.1 Airtime Share

Let $(S_1(t), S_2(t), \cdots, S_N(t))$ model the vector of slots assignment at time slot t, where $S_i(t)$ is the number of slots assigned to user i at time slot t. Let $S(t)$ be the total number of slots at time t. Percentage of Airtime Share(AS) of user i at time slot t is defined as

$$\mathsf{A}S_i(t) = \frac{S_i(t)}{S(t)}$$

4.2 Throughput

Throughput of user i at time slot t is defined as

$$\bar{R}_i(t) = \frac{1}{t}\sum_{i=1}^{t} I_{\{useriisscheduled\}}(t)R_i(t)$$

where $R_i(t)$ is maximum rate supported by user i in time slot t.

4.3 Delay

First moment and second moment of the delays of good user are calculated as,

$$Firstmoment = \frac{d_1 + d_2 + d_3 + \cdots + d_n}{n}$$

$$Secondmoment = \frac{d_1^2 + d_2^2 + d_3^2 + \cdots + d_n^2}{n}$$

where d_i is number of slots good user has to wait in order to access the channel after $(i-1)^{th}$ slot assigned to the good user.

n is the total slots given to the good user

CHAPTER 5

Sensitivity Analysis of Opportunistic Schedulers

5.1 Sum Rate Maximization

Theorem 5.1.1 *For a scheduler that maximizes sum rate, the malicious user can maximize its channel access (in terms of time share) by reporting a large channel value in all the slots. The time share of the regular users can be made arbitrarily small for the setup.*

Proof for $N = 2$ is given and for $N > 2$ similar results hold

Proof Let $(\hat{R}_1(\cdot), \hat{R}_2(\cdot))$ be the reported channel rates of the two users.Assume that $\hat{R}_1(t) = k_1$ for all t. Let $F_2(r) = \mathsf{P}(\hat{R}_2(t) \leq r)$ be the cumulative distribution function of the reported channel of user 2 for all time t.

Sum rate maximization scheduler seeks to maximize the total through put of the system. So it schedules a user with higher rate in every to slot.

$$\text{argmax}\left(\hat{R}_1(t), \hat{R}_2(t)\right)$$

Probability of user 2 scheduled is,

$$1 - F_2(k_1) = \mathsf{P}(\hat{R}_2(t) > k_1)$$

If user 1 reports a constant channel $\hat{R}_2(t) = k_2(> k_1)$ for all t. Probability of user 2 scheduled is,

$$1 - F_2(k_2) = \mathsf{P}(\hat{R}_2(t) > k_2)$$

Since CDF of any distribution is a non-decreasing function and $k_2 > k_1$

$$F_2(k_2) > F_2(k_1)$$

$$1 - F_2(k_2) < 1 - F_2(k_1)$$

choosing k_1 and k_2 in such a way that $\mathsf{P}(k_1 < R_1(t) < k_2)$ is non-zero.

As the constant rate value of malicious user increases, probability of good user chosen for transmission decreases. when k(rate of malicious user) $\rightarrow \infty$, probability of good user chosen goes zero ($\lim_{k\rightarrow\infty}(1 - F_2(k)) = 0$). Which proves the claim.

5.2 Max-Min Fairness

Theorem 5.2.1 *For a scheduler that implements max-min notion of fairness, the malicious user can maximize its channel access (in terms of time share) by reporting a very small channel value in all the slots. The time share of the regular users can be made arbitrarily small for the setup.*

Proof for $N = 2$ is given and for $N > 2$ similar results hold

Proof Let $(\hat{R}_1(\cdot), \hat{R}_2(\cdot))$ be the reported channel rates of the two users. Assume that $\hat{R}_1(t) = k_1$ for all t. Let $\mathsf{E}_2[r] = \int_0^\infty r\mathsf{P}_2(r)\,dx$ be the expected value of user 2's reported rates.

Max-min fairness seeks to increase the lowest through put among user. So it schedules the user with least time average through put till slot t-1 in slot t. As t $\rightarrow \infty$ through put of users will converge to the same value. Let T_1 be air time share of user 1. So we have,

$$k_1 * T_1 = (1 - T_1) * \mathsf{E}[r]$$
$$\frac{k_1}{\mathsf{E}[r]} = \frac{1 - T_1}{T_1}$$

If now user 1 reports a different constant channel $R_2(t) = k_2(< k_1)$. Let the air time share of user 1 be $\hat{T}_1$, Now

$$k_2 * T_1 = (1 - T_1) * \mathsf{E}[r]$$

$$\frac{k_2}{\mathsf{E}[r]} = \frac{1 - \hat{T}_1}{\hat{T}_1}$$

since $k_2 < k_1$,

$$\frac{1-T_1}{T_1} > \frac{1-\hat{T}_1}{\hat{T}_1} \implies \hat{T}_1 > T_1$$

As k decreases air time share of malicious user increase and that of good user decreases. $k \to 0$, $\hat{T}_1 \to 1$. Which proves the claim.

5.3 Proportional Fairness

Theorem 5.3.1 *Let* $N = 2$. *Suppose that a wireless user reports a constant channel to the base station in all the slots. Then, the air time share of the wireless user with proportional fair scheduler is at least* 0.5.

Proof Let $(\hat{R}_1(\cdot), \hat{R}_2(\cdot))$ be the reported channel rates of the two users and without loss of generality assume that $\hat{R}_1(t) = 1$ for all t. Let $F_2(r) = \mathsf{P}(\hat{R}_2(t) \leq r)$ be the cumulative distribution function of the reported channel of user 2 for all time t.

A proportional fair scheduler seeks to maximize sum of logarithms of the long term average throughput of the wireless users. The gradient scheduler that seeks proportional fair operating point is given by

$$\text{argmax}\left(\frac{\hat{R}_1(t)}{\bar{R}_1(t)}, \frac{\hat{R}_2(t)}{\bar{R}_2(t)}\right)$$

where $\bar{R}_i(t) = \frac{1}{t}\sum_{k=1}^{t} I_{\{\text{user } i \text{ is scheduled}\}}(t)\hat{R}_i(t)$. For ergodic channels, the proportional fair scheduler converges to $(\bar{R}_1, \bar{R}_2)$ that maximizes $\log(\bar{R}_1) + \log(\bar{R}_2)$ in the rate region of the wireless network (see Stolyar (2005)).

At the optimal operating point, user 2 is scheduled iff

$$\begin{aligned}
\frac{\hat{R}_1(t)}{\bar{R}_1} &< \frac{\hat{R}_2(t)}{\bar{R}_2} \\
\frac{1}{\bar{R}_1} &< \frac{\hat{R}_2(t)}{\bar{R}_2} \quad \text{(since } \hat{R}_1(t) = 1 \text{ for all } t\text{)} \\
\frac{\bar{R}_2}{\bar{R}_1} &< \hat{R}_2(t)
\end{aligned}$$

Clearly, the policy is a threshold based policy with threshold $\frac{\bar{R}_2}{\bar{R}_1}$. The long term average throughput of user 1, $\bar{R}_1$, is $\bar{R}_1 = F_2(\frac{\bar{R}_2}{\bar{R}_1})$ (as $\bar{R}_1$ is also the fraction of slots allocated to user 1). The long term average throughput of user 2, $\bar{R}_2$, is

$$\bar{R}_2 = \int_{\frac{\bar{R}_2}{\bar{R}_1}}^{\infty} u f_2(u) du \geq \frac{\bar{R}_2}{\bar{R}_1}(1 - F_2(\frac{\bar{R}_2}{\bar{R}_1}))$$

where, $f_2(u)$ is PDF of user 2 and the last expression follows from Markov inequality. Hence, we have,

$$\begin{aligned}
\bar{R}_2 &\geq \frac{\bar{R}_2}{\bar{R}_1}(1 - F_2(\frac{\bar{R}_2}{\bar{R}_1})) \\
1 &\geq \frac{1}{\bar{R}_1}(1 - F_2(\frac{\bar{R}_2}{\bar{R}_1})) \\
\bar{R}_1 &\geq (1 - F_2(\frac{\bar{R}_2}{\bar{R}_1})) \\
F_2(\frac{\bar{R}_2}{\bar{R}_1}) &\geq (1 - F_2(\frac{\bar{R}_2}{\bar{R}_1})) \\
F_2(\frac{\bar{R}_2}{\bar{R}_1}) &\geq \frac{1}{2}
\end{aligned}$$

which proves the result.

Theorem 5.3.2 *Let N=2. Suppose that a wireless user reports a constant channel to the base station in every slot. Than the air time share of the wireless user at best can be* 100%

Proof Proof by Example:

Example 5.3.3 *Let* $(\hat{R}_1(\cdot), \hat{R}_2(\cdot))$ *be the reported channel rates of the two users and without loss of generality assume that* $\hat{R}_1(t) = 1$ *for all* t*. Channel of user 2 is a piecewise function defined as,*

$$R_2(t) = \begin{cases} 1 & \textit{probability } \mathsf{p} \\ 100 & \textit{probability } 1 - \mathsf{p} \end{cases}$$

Figure 5.1 shows the air time share of good user as the probability p *is varied.User with constant channel getting atleast* 50% *when* p *is less than* 0.5*. When* p *is greater than* 0.5*, time share of constant channel user is increasing linearly. But as* $\mathsf{p} \to 1$ *time share won't go to* 100% *in this particular example. After certain* p *it will be again be* 50%*.*

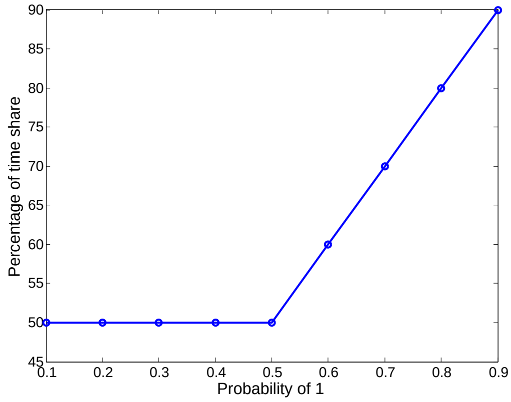


Figure 5.1: Percentage of Time Share vs Probability of Channel state

That p *depends on* $\frac{a}{a+b}$ *ratio, where a,b are the two channel state values and* $a < b$ *. If 'a' and 'b' are chosen properly i.e.* $\frac{a}{a+b} << 1$*, time share of malicious user can be* 100%.

Proposition 5.3.4 *For a scheduler that implements proportional fairness, the malicious user can maximize its channel access (in terms of time share) by reporting a constant channel value in all the slots.*

CHAPTER 6

Performance Evaluation

We have used Rayleigh, Rician and Nakagami fading channel to model channel state.

Raylegih PDF:

$$h(t) = \frac{t}{b^2} e^{\frac{-t^2}{2b^2}}$$

Mean of the random variable is $b\sqrt{\frac{\pi}{2}}$ and variance is $\frac{4-\pi}{2}b^2$. So as the b parameter increaces mean and variance also increases. Figure 6.1 shows probability distribution of rayleigh random variable for different values of 'b'

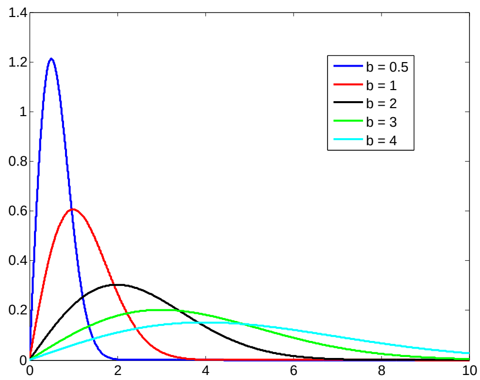


Figure 6.1: Rayleigh Probability Distribution Functions

Rician PDF:

$$h(t) = \mathsf{I}_0\left(\frac{tk}{\sigma^2}\right)\frac{t}{\sigma^2} e^{\frac{-(t^2+k^2)}{2\sigma^2}}$$

As K increases, line of Sight component of signal gets stronger. σ is scaling parameter. Figure 6.2 shows probability distribution of rician random variable for different K and σ.

Nakagami PDF:

$$h(t) = 2\left(\frac{m}{\omega}\right)^m \frac{1}{\Gamma(m)} t^{(2m-1)} e^{\frac{-m}{\omega}t^2}$$

$m = \frac{\mathsf{E}^2[x^2]}{\mathsf{V}ar[x^2]}$ will impact on the shapre of pdf and $\omega = \mathsf{E}[x^2]$ is the spread controlling factor. Figure 6.3 shows the probability distribution of nakagami random variable for different m and ω.

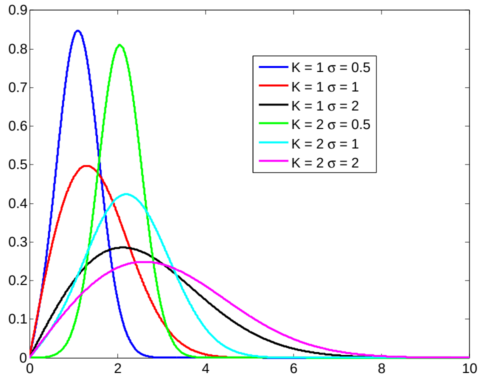


Figure 6.2: Rician Probability Distribution Functions

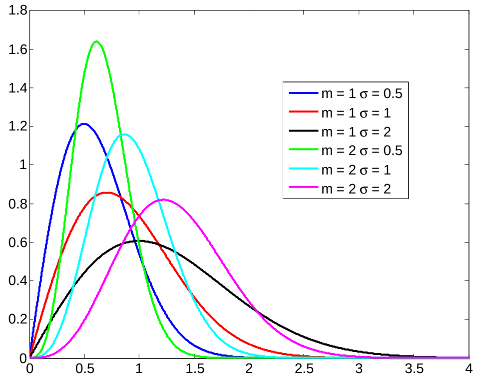


Figure 6.3: Nakagami Probability Distribution Functions

In sections 6.1, 6.2 and 6.3, malicious user has a constant channel of value 1. Maximum supported rate in the slot $R_i(t)$ is calculated as $R_i(t) := W \log\left(1 + \frac{C_i^2(t)}{\sigma^2}\right)$ bits per second (where $W = 5MHz$ is the channel bandwidth and $\sigma^2 = 0.01$ is the AWGN noise power).$C_i^2(t) = |h_i(t)|^2$ because power of transmitted is assumed to be unity. Where $h_i(t)$ can be rayleigh/rician/nakagami fading channel. Number of users in the system is $N = 2$.

6.1 Rayleigh Fading

Figure 6.4 shows the air time share of the good user as the SNR of signal being varied.

Graph shows an increase in time share of the good user when SNR increases. But when SNR is close 3dB, time share of the good user is close to 41%. Which is typically considered as unfair. Point to be noted here is when SNR is close to 1dB, signal power is comparable to noise power. But when the signal power is higher than the noise floor,

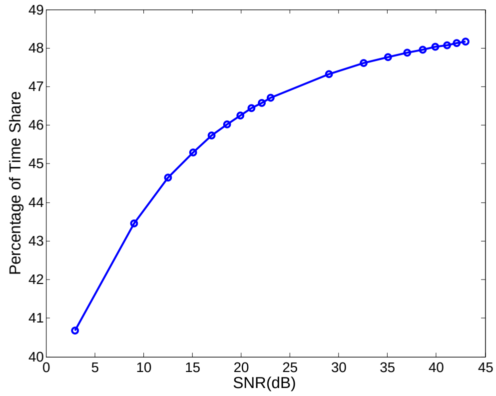
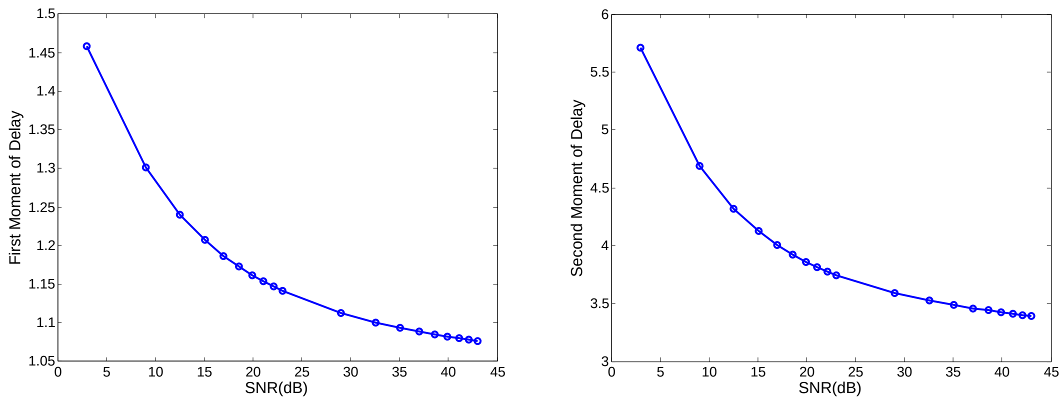


Figure 6.4: Percentage of Time Share VS SNR(rayleigh fading channel)

good user is getting close to 47% which is typically not too unfair. So here in this example PF seems to robust and malicious user may not affect much when the signal power very high compared to noise floor. But the good user is at the cell edge(low signal power), malicious user can affect him badly.

Lesser time share is directly proportional to the delay in accessing the channel. In a two users system and in presence of malicious user first moment of delay should always be great than 1. So as the air time share of the good user increases first moment tends to 1. As SNR increases, air time share of regular user increases so delay moments decreases as a result.

Figure 6.5 shows the first and second moments of delay



(a) First moment of delay (b) Second moment of delay

Figure 6.5: Delay Moments vs SNR(rayleigh fading channel)

Figure 6.6 shows the time averaged throughput of the good user

Increase in throughput is attributed by two factors, increase in air time share of good

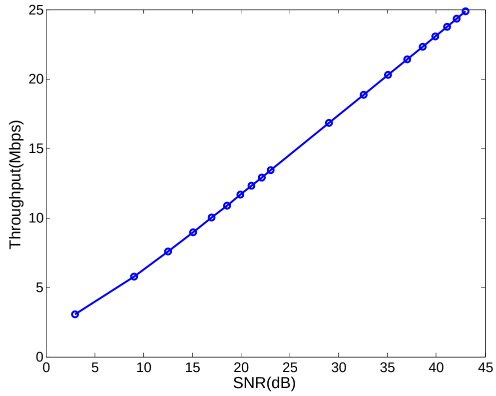


Figure 6.6: Throughput vs SNR(rayleigh fading channel)

user and better channel of good user which also means user can support higher transmission rates.

6.2 Rician Fading

Figure 6.7 shows the air time share of the good user as the Rician K-parameter being varied for different $\sigma' s$ As the non-centrality parameter(k) increases unfairness decreases for the good user.

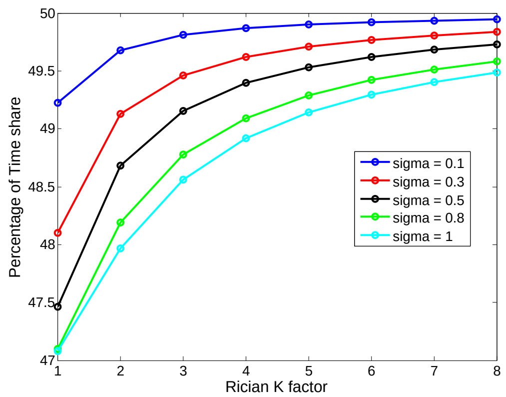


Figure 6.7: Percentage of Time Share vs Rician K factor

Figure 6.8 shows the through put of good user vs non-centrality parameter.

Through put increases because of the better channel good user has.

Figure 6.9 shows first and second moments of delay. As K increases air time share of user increases this implies delay moments of the user should decrease which is seen in Figure 6.9. As the air time share of user approaches 50%, first moment of delay is

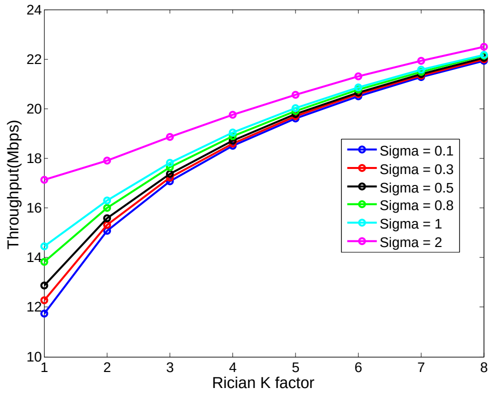
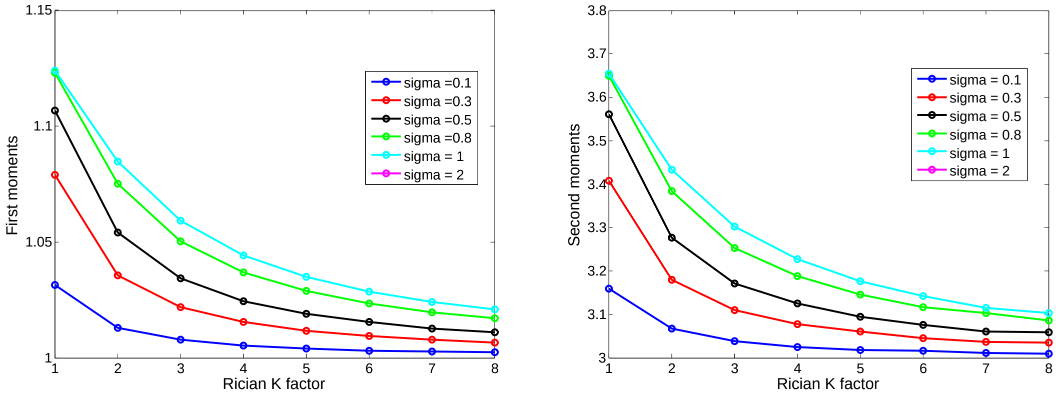


Figure 6.8: Throughput vs Rician K factor

tending to 1 which is the expected result.



(a) First moment of delay

(b) Second moment of delay

Figure 6.9: Delay moments vs Rician K factor

6.3 Nakagami Fading

Figure 6.10 shows the air time share of the good user as the Nakagami m parameter is being varied. There is a increase in the air time share of good user as M increases.

Figure 6.11 shows Air time share of good user when σ is varied with m fixed in a each simulation, varied across simulations. Percentage of Time share increases with increasing σ and as we know from the above plot as M increases time share good user gets better.

As the air time share of the good user increases first moment tends to 1. For a particular value of σ time share is proportional to m-parameter so moments inversely proportional

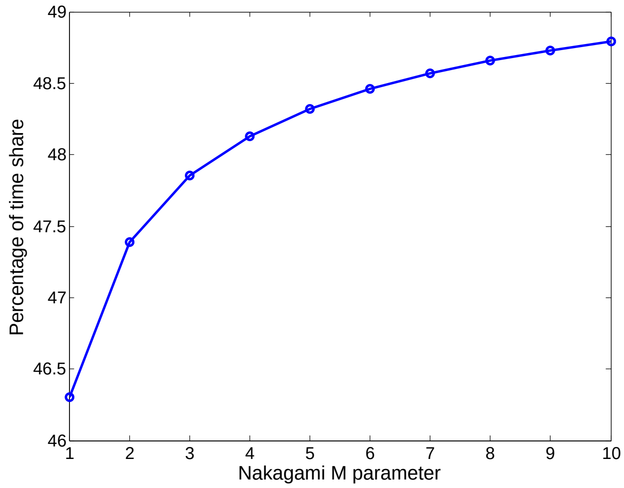


Figure 6.10: Percentage of Time Share vs Nakagami M parameter

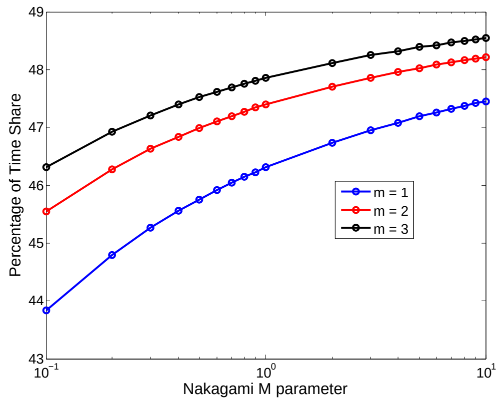
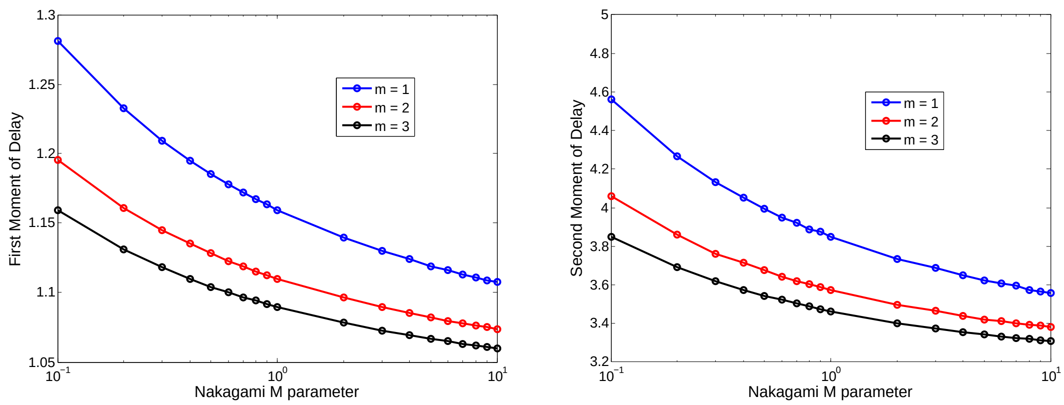


Figure 6.11: Percentage of Time Share vs Nakagami σ parameter

to m-parameter



(a) First moment of delay

(b) Second moment of delay

Figure 6.12: Delay Moments vs Nakagami M parameter

6.4 Single Cell Multiple Users

We need to see the effect of malicious user as the number of good user's increase. N is total number of users in the system contains, N-1 good users and one malicious user. All the good users have iid fading channels. Three fading channel scenarios have been simulated(Rayleigh with Parameter 1, Rician with K=2,$\sigma = 1$ and Nakagami with m=2,$\omega = 1$). Figure 6.13 is the plot between $\frac{100}{N}$ - $air\ time\ share\ of\ good\ user$ (this is lose in air time share for the good user) against N. N is varied from 2 to 10.

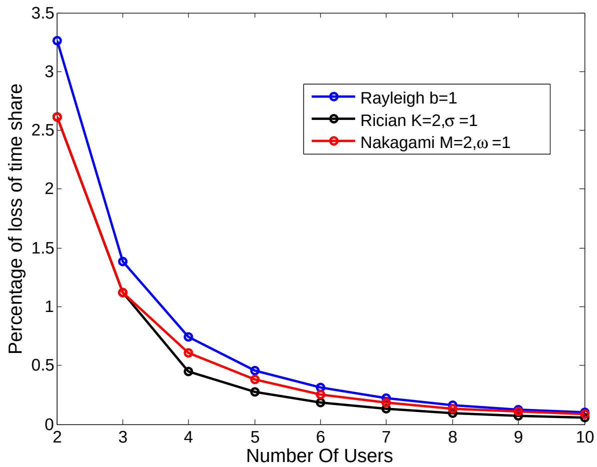


Figure 6.13: Percentage of Time Share vs Number of users

Clearly malicious can not effect Good user in a substantial way as the number of users increase. So PF algorithm seems robust when there are more number of good users or when good users have a better channel.

6.5 Multicell Interference ($N = 2$)

Till now we have been looking at the cases where there is no interference from other base stations expect there is only AWGN noise. It becomes an interesting aspect to see how interference effects the good user.

Frequency reuse ratio is one and only tier-1 interferers are taken into account. Path-Loss exponent for all interferers and good user is assumed to be 2. Signal to interference plus noise ratio in this case will be $SINR(t) = \frac{d_g^2 * h_g^2(t)}{\sum_{k=1}^{6} I_k(t) + \sigma^2}$ (where $I_k(t) = d_k^{-2} * |h_k(t)|^2$ represents power of k^{th} interferer, d_k is the distance between good user and k^{th} interfering BS, d_g is the distance between good user and his BS. $\sigma^2 = 10^{-4}$ is the AWGN noise power).h_k's are iid random variables with rayleigh pdf with same parameter(b = $\frac{1}{\sqrt{2}}$). Radius of cell boundary (inscribed circle of hexagon is approximated as cell) is assumed to be $R = 500m$. Figure 6.14 shows network scenario with interference.

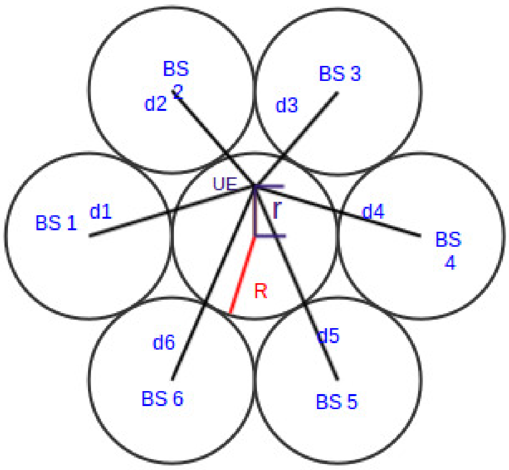


Figure 6.14: Network Scenario with Interference

Maximum supported rate in the slot $R_i(t)$ is calculated as $R_i(t) := W \log\left(1 + SINR(t)\right)$ bits per second (where $W = 5MHz$ is the channel bandwidth). Figure 6.15 shows the variations of air time share of the good user as the BS to good user distance is varied.Three plots shown in the figure 6.15 are with different interference scenarios. Blue graph shows the air time share when there is interference from all 6 tier-1 BS's. Red graph is when we can cancel out the strongest interferer. Black graph is with interference case. As the effect of interference decreases(close to BS) air time share of good user increases. As the distance increases airtime share of the user decreases. Effect of malicious user is more when a user is at cell edge. As we have seen earlier good user gets more airtime share when his channel is better. When distance from BS increases interference increases, so user supposed to get a lower air time share. When user is at cell edge, his air time share close to 37% which is typically unfair. As the user moves away from BS to cell edge there is almost 6% decrement in air time share is seen. So effect of malicious user increases as the user movies close to cell edge.

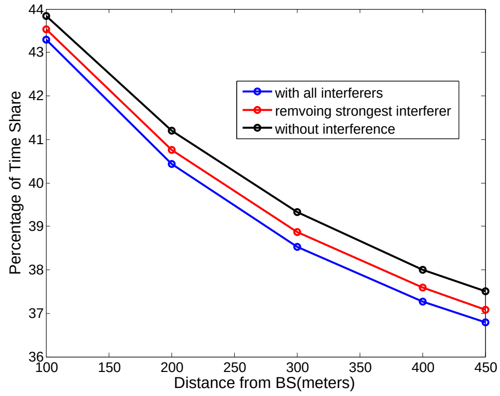


Figure 6.15: Percentage of Time Share vs Distance from BS

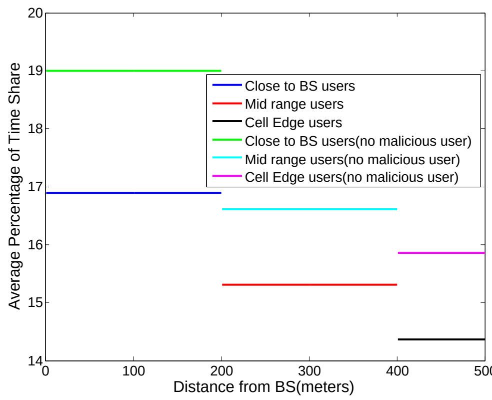
6.6 Multicell Interference ($N > 2$)

When number of users in the system is greater 2 and users are distributed at different locations, effect of malicious user can be different on different users. Each user sees a different channel and different interference power. We have considered two case with $N = 6$ and 11(with 5 and 10 good users). Users are dropped uniformly in the cell. Total cell is sectorized into three parts, if r is the distance of user from BS When $0 \leq r < 200$, user is considered to be close to BS

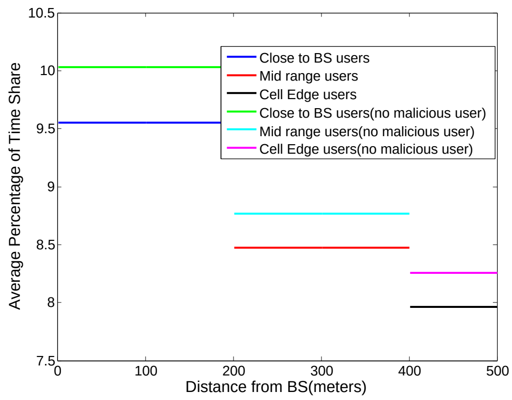
When $201 \leq r < 400$, user is considered to be in the mid range from BS

When $401 \leq r < 500$, user is considered to be at cell

Figure 6.16 shows average air time share of users in different sectors with malicious user and without malicious user in the system with interference from other base stations.



(a) $N = 6$



(b) $N = 11$

Figure 6.16: Average Percentage of Time Share of Users in Different Sectors

With just observing air time share of users with malicious, it seems that malicious user is effecting cell edge user more than user close to base station because average air time share of later is higher. But without malicious user in the system users close to base station are getting higher air time share than users at cell edge, this is because of interference from other cells is very less when user is close to BS. Now the malicious brings down performance of users in all sectors. More importantly decrement in air time share for users close to base station is little more than the decrement of air time share for users at cell edge.

CHAPTER 7

Conclusions

Max-min fair and sum-rate maximization strategies are not robust to attacks from malicious users. Proportional fairness is reasonably robust in terms of isolation. For different scheduling strategies, we identify the worst case performance and the strategy of the malicious user. The performance of a regular user depends on the channel distribution (variability) of the wireless user. The performance of a regular user degrades with decreasing SNR and SINR in the presence of a malicious user. Malicious user brings down performance users at different distances by almost same amount.

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