Impacts of Radio Channel Characteristics, Heterogeneous Traffic Intensity, and Near–Far Effect on Rate Adaptive Scheduling Algorithms

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***Abstract*—Applying adaptive modulation combined with scheduling in a shared data channel can substantially improve the spectral efficiency for wireless systems. This performance gain results from the multiuser diversity, which exploited independent channel variations across multiple users. In this paper, we present a cross-layer analysis to integrate physical-layer channel characteristics, media access control (MAC) layer scheduling strategies, and the network layer issue of heterogeneous traffic intensity across near–far users. Specifically, for radio channel characteristics, we take account of path loss, slowly varying log-normal shadowing and fast-varying Nakagami fading. We also evaluate the impact of selective transmit diversity on the throughput and fairness of wireless data networks. Furthermore, we consider three MAC schedulers: random scheduler, greedy scheduler (GS), and a newly proposed queue-length-based scheduler (QS). By applying the proposed cross-layer analytical framework, the following insights can be gained. First, for the three considered schedulers, channel fluctuations induced by Nakagami fading or log-normal shadowing can improve both total throughput and fairness. Second, using selective transmit diversity can improve throughput, but is unfavorable for the fairness performance. Third, the GS and the QS methods can improve throughput at the expense of unfairness to the far users. However, the throughput improvement from using the GS and the QS decreases as the traffic intensity of the far user increases. In summary, this cross-layer analysis can be used to develop new scheduling mechanisms for achieving better tradeoff between the fairness and throughput for wireless data networks.**

***Index Terms*—Heterogeneous traffic intensity, rate adaptive scheduling, near–far effect.**

I. Introduction

With the growing demand for wireless Internet services, how to improve spectral efficiency for a wireless data transmission has become a crucial issue. One popular approach to achieve high efficiency of the wireless data transmission is to apply the link adaptation technique combined with multiuser scheduling in a shared channel. Many current industrial standards, such as the IS-856 [1] and 3GPP R5 [2], have adopted the link adaptation and scheduling techniques to provide high-speed downlink packet data services.

In the literature, the advantages of applying link adaptation techniques such as adaptive modulation in wireless fading channels have been studied extensively [3]–[5]. In [3], the authors demonstrated that in the single user case, using adaptive modulation can provide more than 5-dB gain over the fixed rate system. The performance improvement of using adaptive modulation can be explained from the water-filling principle of the information theory, i.e., allocating more power to the user when channel quality is good [4]. In [5], the authors compared adaptive modulation and power control from the entire cellular network perspective. In [6], it was shown that additional throughput gain can be achieved by exploiting the multiuser diversity.

While pouring more information bits to the user with better channel quality, the system may immediately face another key issue—how to schedule the transmissions for other users whose channel qualities are poor. Different scheduling strategies can lead to different performance results. One of the major challenges in the design of wireless data networks is to achieve better total throughput and maintain the fairness simultaneously. In the literature, wireless scheduling algorithms can be categorized into two major types according to the considered models. First, the wireless scheduling algorithms in [7] and [8] considered a two-state ON–OFF channel model. Because of its simplicity, the two-state ON–OFF model is suitable for examining the fairness performance of scheduling algorithms. However, using the simple two-state ON–OFF model has limitations in capturing radio channel characteristics. Second, some wireless scheduling algorithms such as [9]–[12] considered a more practical radio channel with emphasis on exploiting the multiuser diversity. In [9]–[12], through Monte Carlo simulations, the authors compared the capacity achieved by several multiuser scheduling algorithms in a practical radio channel assuming that all the users have identical traffic intensity. However, in a system with heterogeneous traffic intensity distribution for the near–far users, the total system throughput may be over estimated if the possible idle periods for the near users are not considered.

In this paper, we present a cross-layer analysis to investigate the joint impacts of radio channel characteristics and heterogeneous traffic intensity on the throughput and fairness performances of rate adaptive scheduling algorithms. Specifically, for the radio channel model, we take account of path loss, slowly

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varying log-normal shadowing and fast-varying Nakagami fading. The suggested channel model can be also used to evaluate the impact of applying selective transmit diversity. As for the media access control (MAC) layer, three schedulers are studied in this paper: 1) random scheduler (RS); 2) greedy scheduler (GS); and 3) our proposed queue-length-based scheduler (QS). Our analysis can also incorporate the impact of heterogeneous traffic intensity and the effect of near–far users.

The contribution of this paper can be summarized as follows. First, we develop an analytical model to jointly investigate the impacts of radio channel characteristics, heterogeneous traffic intensity, and near–far effect on the performance of the rate adaptive wireless scheduling system. Second, based on the observations and results deriving from a simple two-user case considered in this work, this paper provides important system implication and guideline that could be useful in deploying practical wireless data networks. The rest of this paper is organized as follows. In Section II, we describe our physical-layer model, including the channel model, the selective transmit diversity scheme, and adaptive modulation. Section III defines the performance metrics and introduces the data traffic model. In Section IV, we derive the analytical expressions for the throughput and fairness performance for the three considered scheduling disciplines. In Section V, we give numerical results based on our analytical framework. In Section VI, we provide our concluding remarks.

II. Physical-Layer Model

In this section, we describe the radio channel model, selective antenna diversity scheme, and adaptive modulation used in this paper.

A. Channel Model

We assume that the radio link is subject to path loss, log-normal shadowing, and Nakagami multipath fading. Basically, the user far away from the serving base station inherently has a weaker signal strength than that near the base station due to large path loss. The path loss is usually characterized by

$$\mathrm{PL}(r) = 10\alpha \log_{10}\left(\frac{r}{r_0}\right) + L_0 \tag{1}$$

where r is the distance between a transmitter and a receiver, α the path loss exponent, and L_0 the nominal path loss (in decibel) at the known reference distance r_0. For simplicity, we assume $r_0 = 1$ km. In addition to path loss, the received signals fluctuate around the distance-dependent mean value because of the time-varying characteristics of wireless environments. Nakagami and log-normal distributions are widely used to model the fast-varying fading and slowly varying shadowing of wireless channels, respectively. Due to shadowing from terrain, building and trees, the shadowed signal power can be modeled by a log-normal random variable with the following probability density function (PDF)

$$f(x) = \frac{\xi}{\sqrt{2\pi}\sigma x} \exp\left(-\frac{(10\log_{10} x - \eta)^2}{2\sigma^2}\right), \qquad x > 0 \tag{2}$$

where $\xi = 10/\ln(10)$, σ, and η are the mean and standard deviation of $10\log_{10} x$ in decibel, respectively. On the other hand, the power of the Nakagami faded signal can be represented by a Gamma distributed random variable with the PDF as

$$f(x) = \left(\frac{m}{\bar{x}}\right)^m \frac{x^{m-1}}{\Gamma(m)} \exp\left(-\frac{mx}{\bar{x}}\right), \qquad x > 0 \tag{3}$$

where $\Gamma(m) = \int_0^\infty t^{m-1}e^{-t}dt$, m is the Nakagami fading parameter, and $\bar{x}$ is the average received power. When $m = 1$, the Nakagami fading channel is identical to the Rayleigh fading channel. When $m > 1$, the Nakagami distribution can model the fading channel containing a specular or line-of-sight (LOS) component.

The distribution of the link gain G at a distance r with Nakagami fading and log-normal shadowing can be represented by a composite Gamma-log-normal distribution, i.e.,

$$f_G(g) = \int_0^\infty \left(\frac{m}{\omega}\right)^m \frac{g^{m-1}}{\Gamma(m)} \exp\left(-\frac{mg}{\omega}\right) \times \frac{\xi}{\sqrt{2\pi}\sigma\omega} \exp\left(-\frac{(10\log_{10}\omega - \eta)^2}{2\sigma^2}\right) d\omega \tag{4}$$

where $\eta = -10\alpha\log_{10}(r) - L_0$, and the other parameters are defined in (1) and (2). According to [13], the composite Gamma-log-normal distribution can be approximated by another log-normal distribution with the modified mean η_G and standard deviation σ_G as follows:

$$\eta_G = E[10\log_{10} G] = -10\alpha\log_{10}(r) - L_0 + \tilde{\eta}(m) \tag{5}$$

and

$$\sigma_G^2 = \mathrm{Var}[10\log_{10} G] = \sigma^2 + \tilde{\sigma}^2(m). \tag{6}$$

Note that $\tilde{\eta}(m)$ and $\tilde{\sigma}^2(m)$ are given by

$$\begin{aligned}\tilde{\eta}(m) &= \xi\left[\psi(m) - \ln(m)\right]\\ \tilde{\sigma}^2(m) &= \xi^2\zeta(2,m)\end{aligned} \tag{7}$$

where $\psi(m) = -0.5772 + \sum_{j=1}^{m-1} 1/j$ is the Euler psi function and $\zeta(2,m) = \sum_{j=0}^{\infty} 1/(m+j)^2$ is the Riemann's zeta function [18]. For Rayleigh fading with $m = 1$, $\tilde{\eta} = -2.5$ and $\tilde{\sigma}^2 = 31$. When the fading channel contains a LOS component with $m = 8$, $\tilde{\eta} = -0.28$ and $\tilde{\sigma}^2 = 2.5$.

We focus on a simple two-user model to gain insights into the impact of the radio channel characteristics, heterogeneous traffic intensity, and near–far effect on the performance of the wireless scheduling system. Two users (denoted as users 1 and 2) are located at a distance of r_1 and r_2 to the serving base station, respectively. Without loss of generality, we assume that user 1 is closer to the base station than user 2, i.e., $r_2 \geq r_1$. Denote P_t as the transmitting power of the base station and N_0 as the thermal noise power. Then, the received signal-to-noise ratio (SNR) at the kth user is given by

$$\gamma_k(r_k) = \frac{P_\mathrm{t} G(r_k)}{N_0}, \quad k = 1, 2. \tag{8}$$

In (8), because $G(r_k)$ is a log-normal random variable, we can express $\gamma_k(r_k)$ by another log-normal random variable with a modified mean and the same standard deviation. Thus, the mean and the standard deviation of $10\log_{10}\gamma_k(r_k)$ can be written as follows:

$$\eta_{\gamma_k} = -10\alpha\log_{10}(r_k) - L_0 + \tilde{\eta}(m) + 10\log_{10}\left(\frac{P_{\rm t}}{N_0}\right) \quad (9)$$

and

$$\sigma^2_{\gamma_k} = \sigma^2_k + \tilde{\sigma}^2(m). \quad (10)$$

Applying this composite Gamma-log-normal channel model yields the average received SNR of user k by taking the expectation with respect to γ_k, i.e.,

$$E[\gamma_k] = \int_0^\infty \frac{\xi}{\sqrt{2\pi}\sigma_{\gamma_k}\gamma}\exp\left(-\frac{(10\log_{10}(\gamma)-\eta_{\gamma_k})^2}{2\sigma^2_{\gamma_k}}\right)\cdot\gamma d\gamma$$
$$= \exp\left(\frac{\eta_{\gamma_k}}{\xi} + \frac{\sigma^2_{\gamma_k}}{2\xi^2}\right) \equiv \bar{\gamma}_k, \qquad k=1,2. \quad (11)$$

From (9) and (11), it is obvious that the near user, i.e., user 1, has better average SNR than user 2 because of less path loss (near–far effect). However, with time-varying channel fluctuations superimposed on the distance-dependent path loss, the channel quality of the far user can still possibly exceed that of the near one. Assume that the two users separated by a distance $d = r_2/r_1$ encounter uncorrelated fading and shadowing. Let

$$\sigma_{\rm c} = \sqrt{\sigma^2_{\gamma_1} + \sigma^2_{\gamma_2}} = \sqrt{\sigma^2_1 + \sigma^2_2 + 2\tilde{\sigma}^2(m)}. \quad (12)$$

Then, from (8), the probability that the received SNR of user 2 is higher than that of user 1 can be computed by

$$\Pr\{\gamma_2 > \gamma_1\} = \Pr\{\gamma_2 - \gamma_1 > 0\} = Q\left(\frac{10\alpha}{\sigma_{\rm c}}\log_{10}(d)\right) \quad (13)$$

where $Q(\cdot)$ is defined as

$$Q(x) = \int_x^\infty \frac{1}{\sqrt{2\pi}}e^{-t^2/2}dt. \quad (14)$$

Because $Q(\cdot)$ is a monotonically decreasing function, (13) implies that a larger d yields a lower probability that the far user's channel quality exceeds the near user's. However, channel variations resulting from shadowing or fading may possibly offset the near–far effect. Essentially, it is the independent channel fluctuations across the near–far users to allow scheduling techniques to improve the total throughput. We will discuss the scheduling techniques in more details in Section IV.

B. Selective Transmit Diversity

Antenna diversity is known to be an effective technique to enhance the radio link quality. The diversity gain is achieved by employing multiple spatially independent antennas at the transmitter or the receiver. Here, we consider the selective transmit diversity scheme and evaluate its impact on the wireless network with rate adaptive scheduling under Rayleigh fading.

Assume that the base station employs L spatially separated antennas with independent fading. By monitoring the pilot signals, the user can select the antenna with the best signal quality. For a Rayleigh fading channel, the PDF of the effective link gain in (4) can be expressed as [13]

$$f_G(g) = \int_0^\infty \left(\frac{L}{\omega}\right)\exp\left(-\frac{g}{\omega}\right)\left(1-\exp\left(-\frac{g}{\omega}\right)\right)^{L-1}$$
$$\times\frac{\xi}{\sqrt{2\pi}\sigma\omega}\exp\left(-\frac{(10\log_{10}\omega-\eta)^2}{2\sigma^2}\right)d\omega. \quad (15)$$

For $L = 2$ or 3, it was shown in [14] that the distribution in (15) can be approximated by a log-normal distribution but with the modified mean and standard deviation. In this case, the constants $\tilde{\eta}$ in (5) and $\tilde{\sigma}^2$ in (6) become $\tilde{\eta} = 0.5$ and $\tilde{\sigma}^2 = 12.9$ for $L = 2$, whereas $\tilde{\eta} = 0.75$ and $\tilde{\sigma}^2 = 8.46$ for $L = 3$. Compared with the single antenna case, applying selective antenna diversity yields a larger $\tilde{\eta}$ and smaller $\tilde{\sigma}^2$. From (13), we see that the increase of $\tilde{\eta}$ dose not affect the probability $\Pr\{\gamma_2 > \gamma_1\}$ but the reduced dynamic range of channel fluctuations is unfavorable for the far user to compete for services against the near user. Nevertheless, this is observed only from the radio link standpoint. It is important to further consider the impact of traffic intensities as well as scheduling policies.

C. Adaptive Modulation

Once the target user is selected, rate adaptive techniques are used to improve the deliverable link throughput. Such techniques have been widely adopted in current wireless data networks [1], [2]. In this paper, we assume that an adaptive m-ary quadratic-amplitude modulation (QAM) is used for simplicity. Accordingly, it is reasonable to expect that the deliverable throughput is proportional to the received SNR of the target user. From [5], the throughput delivered from the base station to the target user k can be expressed by

$$T_k(\gamma_k) = \log_2(1 + c\gamma_k) \quad (16)$$

where the constant $c = -1.5/\ln(5\cdot\text{BER})$ and the bit-error-rate (BER) is the predetermined bit error rate requirement for the wireless link.

III. Data Traffic Model and Performance Metrics

In this section, we discuss the data traffic model and the performance metrics used in this paper. In [22]–[25], the Markov analysis is performed to evaluate the performance of wireless data networks with various call admission control algorithms. For tractability in mathematical analysis, we will also use Markovian processes to model the behavior of the wireless data network with channel-aware scheduling functions.

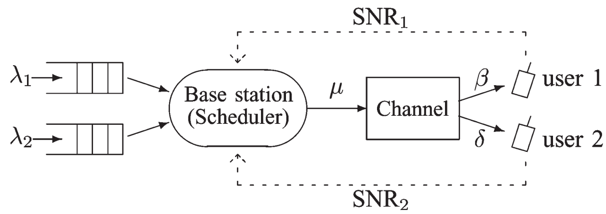

Fig. 1. Illustrative block diagram for the operation of the wireless data network.

A. Data Traffic Model

To assess the throughput and fairness performance of a wireless system with adaptive modulation and scheduling, it is crucial to consider the impact of heterogeneous traffic intensity across the near user and the far user. For example, if we do not consider the possible idle periods for the near user, the total throughput may be over estimated.

In Fig. 1, the packets of users 1 and 2 are generated by independent Poisson arrival processes with the average arrival rates λ_1 and λ_2, respectively. Each user is assumed to track its channel variations via a common pilot channel and correctly feed back to the base station without delay. In turn, the base station has to select either user 1 or 2 for transmissions based on their channel quality and scheduling priority at each time slot. Let (i,j) denote the system state of users 1 and 2 having i and j packets in their queue, respectively. Then, the state space can be written as

$$S = \{(i,j) | 0 \le i \le K_1, 0 \le j \le K_2\} \tag{17}$$

where K_1 and K_2 denote the queue size of users 1 and 2, respectively. The service time of one packet at the base station is assumed to be an exponential distribution with mean service time $1/\mu$. Since the downlink time slots are shared by these two users in a time division manner, the mean service time for the individual user obtained from the server is reduced. Let $f_{ij}^{(k)}$ denote the probability that user k is served at state (i,j) subject to certain scheduling policies. Then, the effective service rate for each user is proportional to the probability of being served. Denote β_{ij} and δ_{ij} as the effective mean service rate of users 1 and 2 at state (i,j), respectively. Then, we have

$$\beta_{ij} = f_{ij}^{(1)} \mu \tag{18}$$

and

$$\delta_{ij} = f_{ij}^{(2)} \mu = \left(1 - f_{ij}^{(1)}\right) \mu. \tag{19}$$

In Appendix A, we will show that the received packets at these two users are two independent Poisson processes with average service rate β_{ij} and δ_{ij}, respectively.

In the equilibrium state, the whole process can be modeled by a two-dimensional birth-and-death Markov chain, as shown in Fig. 2. From the figure, the global balance equation [15] for each state (i,j) is

$$\begin{aligned}(\beta_{ij} + \delta_{ij} + \lambda_1 + \lambda_2)\pi_{ij} &= \lambda_1 \pi_{i-1,j} + \lambda_2 \pi_{i,j-1} \\ &\quad + \beta_{i+1,j}\pi_{i+1,j} + \delta_{i,j+1}\pi_{i,j+1}\end{aligned} \tag{20}$$

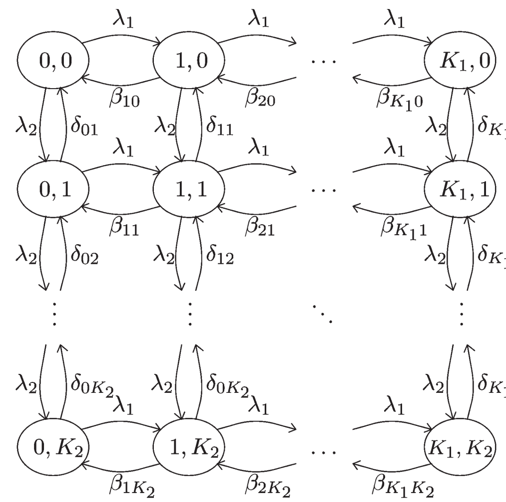

Fig. 2. Markov chain model for the wireless data network with two near–far users.

where π_{ij} is the steady-state probability. In addition, the state probabilities π_{ij} have to satisfy the condition

$$\sum_{(i,j)\in S} \pi_{ij} = 1. \tag{21}$$

In general, it is difficult to get the closed-form expression for π_{ij}. However, it can be solved numerically via (20) and (21). Notice that in Section IV, we will specify $f_{ij}^{(k)}$ according to different scheduling strategies.

B. Performance Metrics

1) Fairness: To begin with, the fairness metric is evaluated by the average probability of a user being served by the base station in this paper. Following the Markovian analysis, the average probability of user k being served (denoted as F_k) can be obtained by summing $f_{ij}^{(k)}$ over all the possible states:

$$F_k = \sum_{i=0}^{K_1} \sum_{j=0}^{K_2} \pi_{ij} f_{ij}^{(k)}. \tag{22}$$

In terms of F_k in (22), we can further compare their relative fairness performance by defining

$$F = \frac{F_1}{F_2}. \tag{23}$$

Obviously, the probability ratio $F > 1$ means that user 1 has higher probability to obtain services from the base station or vice versa.

2) Throughput: Referring to (16), we define the throughput as the average throughput delivered from the base station to users in equilibrium. For an individual user, the throughput of user k then can be written as

$$E[T_k] = \sum_{i=0}^{K_1} \sum_{j=0}^{K_2} \pi_{ij} f_{ij}^{(k)} E\left[T_k | (i,j)\right]. \tag{24}$$

Because T_k is a concave function of γ_k, according to Jensen's inequality, $E[T_k]$ in (24) can be bounded by

$$E[T_k] \leq \sum_{i=0}^{K_1}\sum_{j=0}^{K_2} \pi_{ij} f_{ij}^{(k)} \log_2\left(1 + cE\left[\gamma_k|(i,j)\right]\right) \equiv \overline{T}_k. \tag{25}$$

Finally, the total throughput T is defined as the sum of the average throughput delivered to each user, that is

$$T = E[T_1] + E[T_2]. \tag{26}$$

IV. Scheduling Policy

In the previous section, we have developed an analytical framework to model the packet receiving process of near–far users in a wireless data network with scheduling. In the proposed model, the state transition rates are assumed to be proportional to the probability of user k being served at state (i,j), i.e., $f_{ij}^{(k)}$. Now we specify $f_{ij}^{(k)}$ based on three scheduling policies: the RS, the GS, and the QS.

A. Random Scheduler (RS)

The RS assigns each time slot to the target user in a pseudorandom manner. Thus, in the two-user case, we have

$$f_{ij}^{(1)} = \begin{cases} \frac{1}{2}, & \text{if } i \geq 1, j \geq 1 \\ 1, & \text{if } i \neq 0, j = 0 \\ 0, & \text{if } i = 0. \end{cases} \tag{27}$$

When both queues are empty, we have $f_{ij}^{(1)} = f_{ij}^{(2)} = 0$. When either queue 1 or queue 2 is empty, we assume that the user in the nonempty queue will be definitely served. For the other cases, $f_{ij}^{(2)}$ can be computed easily by $f_{ij}^{(2)} = 1 - f_{ij}^{(1)}$. We note that the RS is similar to the round-robin scheme in [10] and [12].

With the random scheduling policy defined in (27), the fairness metric F_k in (22) can be obtained as

$$F_1 = \frac{1}{2}\sum_{i=1}^{K_1}\sum_{j=1}^{K_2}\pi_{ij} + \sum_{i=1}^{K_1}\pi_{i0} \tag{28a}$$

and

$$F_2 = \frac{1}{2}\sum_{i=1}^{K_1}\sum_{j=1}^{K_2}\pi_{ij} + \sum_{j=1}^{K_2}\pi_{0j}. \tag{28b}$$

Assuming that the channel variation between time slots is independent, the expectation of γ_k at state (i,j) under the RS policy is given by

$$E\left[\gamma_k|(i,j)\right] = \bar{\gamma}_k = \exp\left(\frac{\eta_{\gamma_k}}{\xi} + \frac{\sigma_{\gamma_k}^2}{2\xi^2}\right). \tag{29}$$

Substituting (27) and (29) into (25), the upper bound on throughput is obtained as

$$E[T_1] \leq \log_2(1 + c\,\bar{\gamma}_1)\left(\frac{1}{2}\sum_{i=1}^{K_1}\sum_{j=1}^{K_2}\pi_{ij} + \sum_{i=1}^{K_1}\pi_{i0}\right) \tag{30a}$$

and

$$E[T_2] \leq \log_2(1 + c\,\bar{\gamma}_2)\left(\frac{1}{2}\sum_{i=1}^{K_1}\sum_{j=1}^{K_2}\pi_{ij} + \sum_{j=1}^{K_2}\pi_{0j}\right). \tag{30b}$$

We note that the throughput and fairness performances are jointly determined by channel characteristics γ_i, traffic intensity λ_i and the scheduling policy f_{ij}. Clearly, the main advantage of the RS method is its fairness and simplicity for implementation. However, because of neglecting the link condition among multiple users, the RS method could miss the chance to deliver more bits to the users with good channel quality. Therefore, it is anticipated that the RS method has worse throughput performance compared with other schedulers taking advantage of the link condition among users.

B. Greedy Scheduler (GS)

By contrast, the GS always pursues the maximum total throughput by assigning time slots to the user with the best SNR. In [10], the GS is also called the maximum C/I scheduler. Using the greedy policy, the total throughput is boosted at the expense of sacrificing the fairness to the remote users. Based on the GS policy, we have

$$f_{ij}^{(1)} = \begin{cases} \Pr\{\gamma_1 > \gamma_2\}, & \text{if } i \geq 1, j \geq 1 \\ 1, & \text{if } i \neq 0, j = 0 \\ 0, & \text{if } i = 0. \end{cases} \tag{31}$$

Recalling (13) and $Q(-x) = 1 - Q(x)$, we simplify $\Pr\{\gamma_1 > \gamma_2\}$ as

$$\Pr\{\gamma_1 > \gamma_2\} = Q\left(-\frac{10\alpha}{\sigma_c}\log_{10}(d)\right). \tag{32}$$

Then, from (22), the fairness indexes of users 1 and 2 can be written as

$$F_1 = Q\left(-\frac{10\alpha}{\sigma_c}\log_{10}(d)\right)\sum_{i=1}^{K_1}\sum_{j=1}^{K_2}\pi_{ij} + \sum_{i=1}^{K_1}\pi_{i0} \tag{33a}$$

and

$$F_2 = Q\left(\frac{10\alpha}{\sigma_c}\log_{10}(d)\right)\sum_{i=1}^{K_1}\sum_{j=1}^{K_2}\pi_{ij} + \sum_{j=1}^{K_1}\pi_{0j}. \tag{33b}$$

Under the greedy policy (31), we have

$$E\left[\gamma_k|(i,j)\right] = \begin{cases} E[\gamma_1|\gamma_1 > \gamma_2], & \text{if } k = 1 \\ E[\gamma_2|\gamma_2 > \gamma_1], & \text{if } k = 2. \end{cases} \tag{34}$$

The average conditional SNR of (34) can be calculated by the following proposition.

Proposition 1: Let $Y_A = 10^{X_A/10}$ and $Y_B = 10^{X_B/10}$ denote two independent log-normal random variables with $X_A = \mathcal{N}(\eta_A, \sigma_A^2)$ and $X_B = \mathcal{N}(\eta_B, \sigma_B^2)$, where $\mathcal{N}(\eta, \sigma^2)$ denotes a Gaussian random variable with mean η and standard deviation σ. Let $\sigma = \sqrt{\sigma_A^2 + \sigma_B^2}$. Then, the mean of Y_A conditioned on $Y_A > Y_B$ is

$$E[Y_A|Y_A > Y_B] = \exp\left(\frac{\eta_A}{\xi} + \frac{\sigma_A^2}{2\xi^2}\right) \cdot Q\left(\frac{\eta_B - \eta_A - \sigma_A^2/\xi}{\sigma}\right) \Big/ Q\left(\frac{\eta_B - \eta_A}{\sigma}\right). \quad (35)$$

Proof: Please refer to Appendix B. ■

Substituting (34) to (25), the throughput performance of individual users with the GS can be written as

$$\overline{T}_1 = \log_2(1 + cE[\gamma_1|\gamma_1 > \gamma_2])\, Q\left(-\frac{10\alpha}{\sigma_c}\log_{10}(d)\right) \cdot \sum_{i=1}^{K_1}\sum_{j=1}^{K_2}\pi_{ij} + \log_2(1 + c\,\bar{\gamma}_1)\sum_{i=1}^{K_1}\pi_{i0} \quad (36a)$$

and

$$\overline{T}_2 = \log_2(1 + cE[\gamma_2|\gamma_2 > \gamma_1])\, Q\left(\frac{10\alpha}{\sigma_c}\log_{10}(d)\right) \cdot \sum_{i=1}^{K_1}\sum_{j=1}^{K_2}\pi_{ij} + \log_2(1 + c\,\bar{\gamma}_2)\sum_{j=1}^{K_2}\pi_{0j}. \quad (36b)$$

The conditional mean in (36a) and (36b) can be given by using Proposition 1:

$$E[\gamma_1|\gamma_1 > \gamma_2] = \bar{\gamma}_1\, Q\left(-\frac{10\alpha}{\sigma_c}\log_{10}(d) - \frac{\sigma_{\gamma_1}^2}{\xi\sigma_c}\right) \Big/ Q\left(-\frac{10\alpha}{\sigma_c}\log_{10}(d)\right) \quad (37a)$$

and

$$E[\gamma_2|\gamma_2 > \gamma_1] = \bar{\gamma}_2\, Q\left(\frac{10\alpha}{\sigma_c}\log_{10}(d) - \frac{\sigma_{\gamma_2}^2}{\xi\sigma_c}\right) \Big/ Q\left(\frac{10\alpha}{\sigma_c}\log_{10}(d)\right). \quad (37b)$$

C. Queue-Length-Based Scheduler (QS)

Unlike the GS policy that places emphasis only on SNR, we propose a QS to consider both the radio channel condition and the waiting queue behavior. The concept of the QS is similar to that of the modified-largest-weighted-delay-first (MLWDF) scheduling algorithm [19], [20] in that both the scheduling policies consider the current channel conditions as well as the states of the queues in deciding the target user. However, the QS policy gives more flexibility to raise the priority of the user with longer queue length by introducing an Ω parameter. According to the QS, either the user with better link quality or the user with longer queue length can raise priority. Specifically, the QS policy is defined by

$$f_{ij}^{(1)} = \begin{cases} \Pr\left\{\frac{\gamma_1}{\gamma_2} > \left(\frac{j}{i}\right)^{\Omega}\right\}, & \text{if } i \geq 1, j \geq 1 \\ 1, & \text{if } i \neq 0, j = 0 \\ 0, & \text{if } i = 0 \end{cases} \quad (38)$$

where $\Omega \geq 0$ is an empirical constant to raise the priority of the far user 2. When the waiting queue length of user 2 is longer than that of user 1, e.g., $j/i = 2$, the SNR of user 1 has to be 2^{Ω} times higher than that of user 2 in order to obtain the services. The QS becomes the GS if $\Omega = 0$. In other words, the QS provides a mechanism to balance the total throughput and fairness. Similar to (32), (38) can be derived as

$$\Pr\left\{\frac{\gamma_1}{\gamma_2} > \left(\frac{j}{i}\right)^{\Omega}\right\} = Q\left(-\frac{10}{\sigma_c}\log_{10}\left\{\left(\frac{i}{j}\right)^{\Omega} d^{\alpha}\right\}\right). \quad (39)$$

Then, under the QS policy, we have the fairness expression for each user as follows:

$$F_1 = \sum_{i=1}^{K_1}\sum_{j=1}^{K_2} Q\left(-\frac{10}{\sigma_c}\log_{10}\left\{\left(\frac{i}{j}\right)^{\Omega} d^{\alpha}\right\}\right)\pi_{ij} + \sum_{i=1}^{K_1}\pi_{i0} \quad (40a)$$

and

$$F_2 = \sum_{i=1}^{K_1}\sum_{j=1}^{K_2} Q\left(\frac{10}{\sigma_c}\log_{10}\left\{\left(\frac{i}{j}\right)^{\Omega} d^{\alpha}\right\}\right)\pi_{ij} + \sum_{j=1}^{K_2}\pi_{0j}. \quad (40b)$$

Besides, the throughput expression for each user can be given by

$$\overline{T}_1 = \sum_{i=1}^{K_1}\sum_{j=1}^{K_2}\pi_{ij} f_{ij}^{(1)} \log_2\left(1 + cE\left[\gamma_1|\gamma_1 > \gamma_2\left(\frac{j}{i}\right)^{\Omega}\right]\right) + \log_2(1 + c\,\bar{\gamma}_1)\sum_{i=1}^{K_1}\pi_{i0} \quad (41a)$$

and

$$\overline{T}_2 = \sum_{i=1}^{K_1}\sum_{j=1}^{K_2}\pi_{ij} f_{ij}^{(2)} \log_2\left(1 + cE\left[\gamma_2|\gamma_2 > \gamma_1\left(\frac{i}{j}\right)^{\Omega}\right]\right) + \log_2(1 + c\,\bar{\gamma}_1)\sum_{j=1}^{K_1}\pi_{0j}. \quad (41b)$$

Again, from Proposition 1, the conditional mean in (41a) and (41b) can be written as

$$E\left[\gamma_1|\gamma_1 > \gamma_2\left(\frac{j}{i}\right)^{\Omega}\right] = \bar{\gamma}_1 Q\left(-\frac{10}{\sigma_c}\log_{10}\left\{\left(\frac{i}{j}\right)^{\Omega} d^{\alpha}\right\} - \frac{\sigma_{\gamma_1}^2}{\xi\sigma_c}\right) \Big/ Q\left(-\frac{10}{\sigma_c}\log_{10}\left\{\left(\frac{i}{j}\right)^{\Omega} d^{\alpha}\right\}\right) \quad (42a)$$

and

$$E\left[\gamma_2|\gamma_2>\gamma_1\left(\frac{i}{j}\right)^{\Omega}\right]=\bar{\gamma}_2 Q\left(\frac{10}{\sigma_{\rm c}}\log_{10}\left\{\left(\frac{i}{j}\right)^{\Omega}d^{\alpha}\right\}-\frac{\sigma_{\gamma_2}^2}{\xi\sigma_{\rm c}}\right)\Bigg/ Q\left(\frac{10}{\sigma_{\rm c}}\log_{10}\left\{\left(\frac{i}{j}\right)^{\Omega}d^{\alpha}\right\}\right). \quad (42b)$$

So far, we have provided the performance analysis for the wireless scheduling system with two near–far users under the RS, GS, and QS polices. Now, we take the QS scheduling policy as an example to sketch an outline of how to extend the previous analysis to the multiple-user case. Let γ_k denote the received SNR for user k $(k = 1,\ldots,M)$. Let $(n_1, n_2,\ldots,n_M)$ be the system state denoting that user k has n_k packets in its queue. Then, the probability that user k is served at state $(n_1, n_2,\ldots,n_M)$ in (38) can be generalized to $f^{(k)}_{(n_1,\ldots,n_M)} = \Pr\{\gamma_k n_k^{\Omega} > \gamma_i n_i^{\Omega} \text{ for all } i \neq k\}$. The average probability of user k being served can be expressed by $F_k = \sum_{n_1=0}^{K_1}\cdots\sum_{n_M=0}^{K_M}\pi_{(n_1,\ldots,n_M)}f^{(k)}_{(n_1,\ldots,n_M)}$, where K_k denotes the queue size of user k and $\pi_{(n_1,\ldots,n_M)}$ is the steady-state probability. Analogous to (20) and (21), one can write down the global balance equation and normalization condition for the M-dimensional Markov chain to solve the steady-state probability $\pi_{(n_1,\ldots,n_M)}$. Similarly, the average throughput for user k and the total system throughput can be, respectively, written by $E[T_k] = \sum_{n_1=0}^{K_1}\cdots\sum_{n_M=0}^{K_M}\pi_{(n_1,\ldots,n_M)}f^{(k)}_{(n_1,\ldots,n_M)} E[T_k|(n_1,\ldots,n_M)]$ and $T = \sum_{k=1}^{M}E[T_k]$ for the multiple-user case. We note that although it may be difficult to get the closed-form expression for $f^{(k)}_{(n_1,\ldots,n_M)}$ when $M > 2$, one can use numerical simulations to obtain the result of the multiple-user case. In the next section, we will show some numerical results based on the simple two-user model to gain insights into the impact of the radio channel characteristics, heterogeneous traffic intensity, and near–far effect on the performance of the wireless scheduling system.

V. Numerical Results

In this section, we apply the proposed analytical framework to get some numerical results to illustrate the joint effects of the scheduling policy, traffic intensity, and radio channel characteristics on the throughput and fairness performances of wireless data networks. The following parameters are used in obtaining the numerical results: $P_{\rm t} = 40$ dBm, $L_0 = 128$ dB,[1] $N_0 = -100$ dBm, $\alpha = 4$, $\sigma_1 = \sigma_2 = 8$, $m = 1$, $K_1 = K_2 = 10$ and, BER $= 10^{-3}$.

A. Effect of the Near–Far Location

Fig. 3 compares the three scheduling policies in terms of throughput and fairness with various separation distances between users. We let $\lambda_1/\mu = \lambda_2/\mu = 1.25$, fix the location of user 1 at $r_1 = 0.3$ km, and change the location of user 2 from r_1 to $6r_1$. In Fig. 3(a), the fairness ratio of the QS increases marginally and that of the RS remains to be one when $d = r_2/r_1$ varies from 1 to 6. At the same time, the fairness ratio between the two near–far users significantly increases from 1 to 29 for the GS. In Fig. 3(b), as d increases from 1 to 6, the total throughput is dropped by 9%, 19%, 25%, and 42% for the GS, the QS with $\Omega = 30$, the QS with $\Omega = 50$, and the RS, respectively. Overall, this example shows that the GS can provide the largest total throughput by sacrificing the fairness against the far user. In contrast, the RS is a fair scheduler but yields the worst total throughput. The QS, however, provides a balance mechanism to significantly improve the fairness performance over the GS while enhancing the capacity performance over the RS.

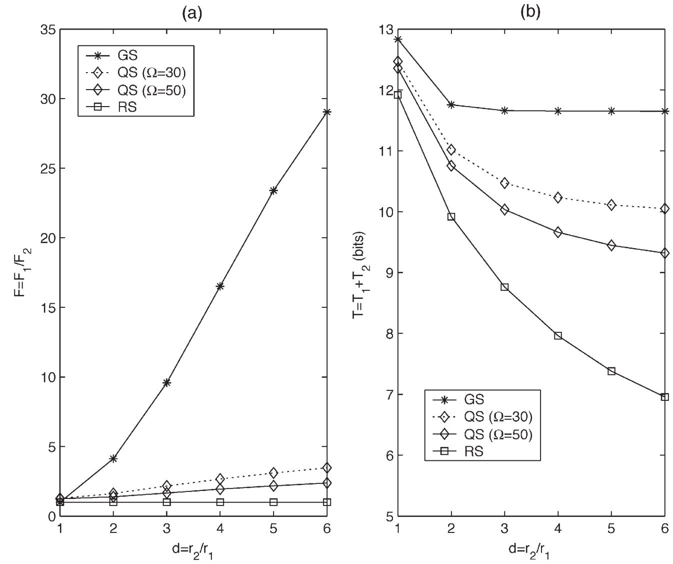

Fig. 3. Effect of near–far locations on the fairness and throughput performance of the wireless data network. Here, GS: greedy scheduler; QS: queue-length-based scheduler; RS: random scheduler. (a) Fairness ratio. (b) Total throughput.

Fig. 4 elaborates the dynamics behind Fig. 3 by showing the fairness and throughput performance with respect to each user. From Fig. 4(a) and (b), one can observe that the GS and the QS increase the probability of user 1 to compete for the services as user 2 moves away from the base station. When $d > 3$, F_1 is higher than 90% for the GS and 60% for the QS, respectively. On the other hand, Fig. 4(c) and (d) show the achievable throughput of the near user and the far user. When user 2 is moving away from the base station, all schedulers deliver less throughput to the far user in Fig. 4(d). In particular, we note that under the RS policy the throughput of user 1 remains constant in Fig. 4(c) but the throughput of user 2 decreases with the increasing d in Fig. 4(d). As a result, the polite attribute of the RS leads to the decrease of the total throughput in Fig. 3(b) especially when d becomes large. In contrast, the GS and the QS will automatically schedule user 1 more frequently by increasing F_1 when d becomes large. This can explain why the total throughput of the GS and the QS is less sensitive to the movement of user 2 as compared with the RS in Fig. 3(b).

[1] This parameter follows from the Okumura-Hata model for an urban macrocell with the base station antenna height of 30 m, mobile antenna height of 1.5 m, and carrier frequency of 1950 MHz [21].

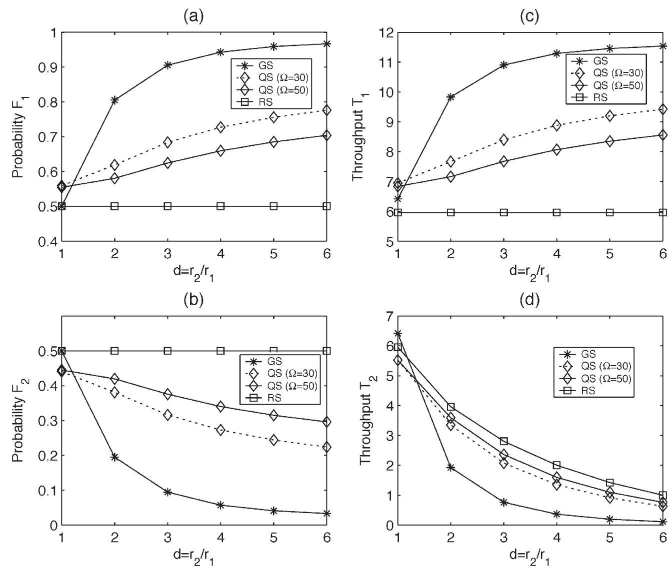

Fig. 4. Effect of near–far locations on the fairness and throughput performance of individual users. Here, GS: greedy scheduler; QS: queue-length-based scheduler; RS: random scheduler. (a) Prob. of user 1 being served. (b) Prob. of user 2 being served. (c) Throughput of user 1. (d) Throughput of user 2.

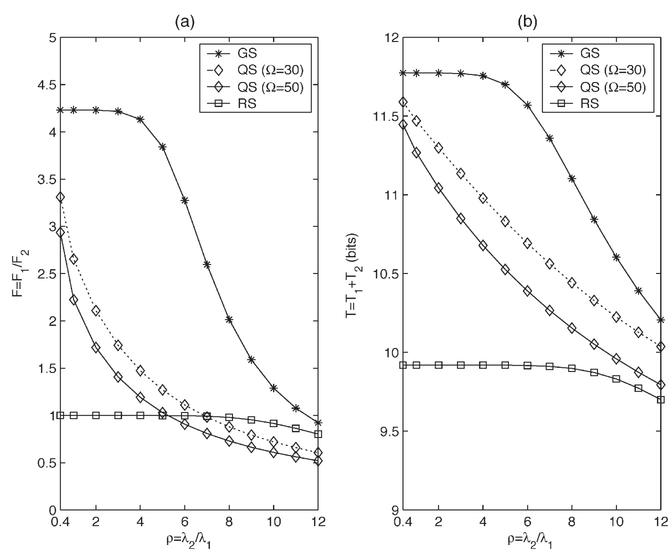

Fig. 5. Effect of heterogeneous traffic intensity on the fairness and throughput performance of the wireless data network. Here, GS: greedy scheduler; QS: queue-length-based scheduler; RS: random scheduler. (a) Fairness ratio. (b) Total throughput.

B. *Effect of Heterogeneous Traffic Intensity*

Fig. 5 illustrates the effect of heterogeneous traffic intensity between near–far users in terms of throughput and fairness. In this example, we fix $(\lambda_1 + \lambda_2)/\mu = 6.25$ while varying the ratio $\rho = \lambda_2/\lambda_1$ from 0.4 to 12. The two users are located at $r_1 = 0.3$ km and $r_2 = 0.9$ km, respectively. From Fig. 5(a), the fairness ratio $F = F_1/F_2$ for the GS and QS decreases considerably when the traffic intensity ratio ρ increases. Although the GS and the QS can favor the near user to compete for the services as long as its queue is nonempty, the asymmetric traffic intensity ratio $\rho > 1$ would demand that the base station arrange more transmissions to the far user. At $\rho = 11.8$ for the GS or $\rho = 5$ for the QS ($\Omega = 50$), the two users have equal probability to obtain the downlink transmissions. When $\rho > 11.8$ for the GS and $\rho > 5$ for the QS ($\Omega = 50$), F becomes smaller than one. This implies that the far user with heavier traffic intensity can have higher chances to receive the services, thereby improving the unfairness situation between the near–far users. We note that the value of F remains to be one but slightly decreases at about $\rho = 8$ for the RS in Fig. 5(a).

In Fig. 5(b), comparing the total throughput at $\rho = 1$ (uniform traffic intensity) with that at $\rho = 12$, we observe that the total throughput degrades with the increasing ρ for all the three scheduling policies. Because the near user usually results in higher throughput than the far user, the decrease of F_1 and the increase of F_2 in Fig. 5(a) due to heterogeneous traffic intensity lead to the decrease of the total throughput in Fig. 5(b). It is also shown that the total throughput achieved by the GS and QS decreases more apparently than the RS with the increasing ρ. As the traffic intensity of the far user is much higher than that of the near user, all the three schedulers have similar performances.

The system implication from the observations of Fig. 3 and Fig. 5 is made as follows. When a cell has nonuniform traffic distribution, e.g., a hot spot zone within a cell, the location of the base station has a critical effect on the resulting throughput performance of the wireless data system with rate adaptive scheduling algorithms. It is suggested to deploy the base station near the area with heavier traffic demand if high system throughput is the major concern. On the contrary, if the base station is deployed far from the high traffic demand area, applying different scheduling algorithms such as the GS may have only limited benefits on the improvement of the system throughput.

C. *Effect of Channel Characteristics and Selective Transmit Diversity*

Fig. 6 illustrates the impact of radio channel characteristics and selective transmit diversity on the wireless data networks with scheduling. Take the curve with $\sigma_1 = \sigma_2 = 8$, $m = 1$, and $L = 1$ as the baseline case. When the Nakagami parameter m is changed to an environment with a strong LOS component, e.g., $m = 8$, it is interesting to note that both the throughput and the fairness performance of all the three schedulers are degraded. In the LOS environment with milder channel variations, the SNR of the far user has a lower probability to exceed that of the near user, as illustrated by (13). Hence, a bias against the far user is more apparent, thereby leading to the worse fairness performance in the LOS environment, as shown in Fig. 6(a). On the other hand, in a channel with large fluctuations, the scheduling algorithms are more likely to take advantage of the multiuser diversity to serve the target user at the higher peaks of the radio channel. Consequently, the system throughput is reduced with a large m, as shown in Fig. 6(b). The same arguments apply to account for the effect of channel shadowing on the throughput and fairness performances, as shown in Fig. 6. Therefore, it is concluded that channel fluctuations induced by Nakagami fading as well as log-normal shadowing can improve both the total throughput and fairness performance when a proper scheduling algorithm is designed to exploit the multiuser diversity.

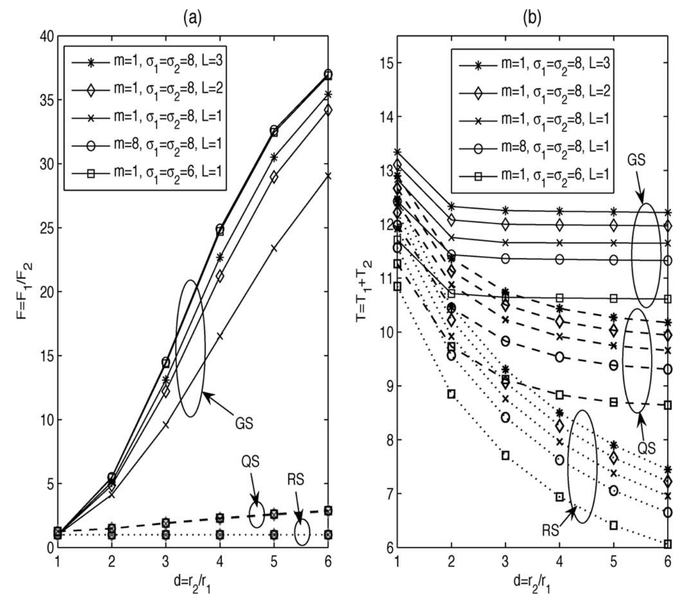

Fig. 6. Effect of log-normal shadowing and Nakagami fading on the fairness and throughput performance of the wireless data network ($\Omega = 40$). Here, GS: greedy scheduler; RS: random scheduler; m: Nakagami fading parameter; σ: log-normal shadowing standard deviation; L: number of antennas at the base station. (a) Fairness comparison. (b) System throughput.

Furthermore, we investigate the performance of applying the selective transmit diversity technique in the wireless scheduling system. It is known from Section II-B that applying the selective transmit diversity technique has the effect of enhancing the mean received SNR and reducing the channel variations. The smaller channel variations make the far user more difficult to compete for the services than the near user. Thus, the fairness ratio increases with the larger L, as shown in Fig. 6(a). On the other hand, the combined effect of the higher mean and smaller variation in the received SNR improves the total throughput in Fig. 6(b). In brief, applying the selective transmit diversity is beneficial to the throughput performance but is harmful to the fairness.

We note that the impact of channel characteristics is evaluated under the assumption of no channel imperfections such as correlated channel states between time slots or channel estimation error. When the inevitable channel imperfections occur in practical systems, it is expected that the performance of the GS could be most sensitive to these imperfections since its scheduling policy is totally related to the channel states. On the contrary, the RS could be least sensitive to the channel imperfections since its scheduling policy has nothing to do with the channel states.

VI. Conclusion

In this paper, we have presented a new analysis to investigate the joint impacts of radio channel characteristics, heterogeneous traffic intensity, and near–far effect on the throughput and fairness performances of rate adaptive scheduling algorithms. Our analysis integrates the effects from both the physical layer and the MAC layer. From the physical-layer standpoint, we take account of path loss, log-normal shadowing, and Nakagami fading. The effect of applying selective transmit diversity on the system performance is also assessed. From the MAC layer perspective, we model three different scheduling policies and incorporate the impact of heterogeneous traffic intensity. Based on the numerical results, we can make the following conclusions.

1) If a scheduler is employed to take advantage of the multiuser diversity, channel fluctuations induced by Nakagami fading or log-normal shadowing can improve both total throughput and fairness performance. On the other hand, using selective transmit diversity is only beneficial for the throughput performance but is adverse for the fairness performance.
2) When all the users in a cell demand high traffic, the total throughput is contributed mainly by those users close to the base station. Under such a circumstance, if most users are located on the cell fringe, applying the RS policy may decrease the total throughput compared with the GS and the QS.
3) The GS and the QS methods improve the throughput performance at the expense of being unfair to the far users. However, this improvement diminishes as the traffic intensity for the far user is much larger than the near user.

In order to gain insights into the impact of radio channel characteristics on the performance of the wireless scheduling system, we have assumed no channel imperfections such as correlated channel states and channel estimation errors for wireless scheduling in this paper. Thus, the system throughput obtained in this paper can be regarded as an upper bound (optimistic result) under the perfect channel assumption. In the future, it is worthwhile to further investigate the impacts of channel imperfections on the performance of the wireless scheduling systems. Finally, the introduced cross-layer analysis can be used to develop or evaluate new scheduling schemes, e.g., the QS in this paper, by considering the interaction of the physical-layer characteristics and network traffic intensity.

Appendix A
Data Receiving Processes by Users 1 and 2

In this Appendix, we demonstrate that the processes of the data received by the user 1 and 2 are two independent Poisson processes with mean rate $f_{ij}^{(1)}\mu$ and $(1 - f_{ij}^{(1)})\mu$, respectively. This is one of the important properties of Poisson processes which can be found in [16, Ex. 2.23]. For completeness, we cite this property and include a proof here. Suppose the data arrival N is a Poisson process with mean rate μ. Each data packet is independently selected by the random process N_1 and N_2 with probability f and $1 - f$, respectively. Then, we have

$$\begin{aligned}
&\Pr\{N_1(t) = n_1, N_2(t) = n_2\} \\
&\quad = \Pr\{N(t) = n_1 + n_2\} \\
&\qquad \cdot \Pr\{N_1(t) = n_1, N_2(t) = n_2 | N(t) = n_1 + n_2\} \\
&\quad = \binom{n_1 + n_2}{n_1} f^{n_1}(1-f)^{n_2} \frac{(\mu t)^{n_1+n_2} e^{-\mu t}}{(n_1+n_2)!} \\
&\quad = \frac{(f\mu t)^{n_1} e^{-f\mu t}}{n_1!} \cdot \frac{((1-f)\mu t)^{n_2}\, e^{-(1-f)\mu t}}{n_2!} \\
&\qquad\quad n_1 \geq 0,\ n_2 \geq 0. \qquad (43)
\end{aligned}$$

Upon completion of (43), we can further obtain

$$\Pr\{N_1(t)=n_1\} = \sum_{n_2=0}^{\infty} \Pr\{N_1(t)=n_1, N_2(t)=n_2\} = \frac{(f\mu t)^{n_1} e^{-f\mu t}}{n_1!} \quad (44)$$

and

$$\Pr\{N_2(t)=n_2\} = \sum_{n_1=0}^{\infty} \Pr\{N_1(t)=n_1, N_2(t)=n_2\} = \frac{((1-f)\mu t)^{n_2}\, e^{-(1-f)\mu t}}{n_2!}. \quad (45)$$

From (43) to (45), we conclude the claim.

Appendix B
Derivation of Proposition 1

We begin with the following conditional distribution function

$$F_{Y_A|Y_A>Y_B}(y) = \frac{\Pr\{Y_A>Y_B, Y_A<y\}}{\Pr\{Y_A>Y_B\}} = \frac{\Pr\{X_A>X_B, X_A<10\log_{10} y\}}{\Pr\{X_A>X_B\}}. \quad (46)$$

Equation (46) follows from the strictly increasing property of a logarithm function. Because X_A and X_B are two independent Gaussian random variables, the denominator of (46) can be easily evaluated as

$$\Pr\{X_A>X_B\} = Q\left(\frac{\eta_B-\eta_A}{\sigma}\right) \quad (47)$$

where $\sigma=\sqrt{\sigma_A^2+\sigma_B^2}$. Denoting the joint PDF of the random variables X_A and X_B by $f_{X_AX_B}(x_A,x_B)$, the numerator of (46) can be expressed by

$$\begin{aligned}\Pr\{X_A>X_B, X_A<10\log_{10} y\} &= \int_{-\infty}^{10\log_{10} y}\int_{-\infty}^{x_a} f_{X_AX_B}(x_a,x_b)dx_b dx_a \\ &= \frac{1}{2\pi\sigma_A\sigma_B}\int_{-\infty}^{10\log_{10} y}\int_{-\infty}^{x_a} \exp\left[-\frac{(x_a-\eta_A)^2}{2\sigma_A^2}\right] \cdot \exp\left[-\frac{(x_b-\eta_B)^2}{2\sigma_B^2}\right] dx_b dx_a. \quad (48)\end{aligned}$$

Since the inner integral associated with x_B in (48) can be computed by

$$\frac{1}{\sqrt{2\pi}\sigma_B}\int_{-\infty}^{x_a} \exp\left[-\frac{(x_b-\eta_B)^2}{2\sigma_B^2}\right] dx_b = Q\left(\frac{\eta_B-x_a}{\sigma_B}\right) \quad (49)$$

we can rewrite (48) as

$$\Pr\{X_A>X_B, X_A<10\log_{10} y\} = \frac{1}{\sqrt{2\pi}\sigma_A} \times \int_{-\infty}^{10\log_{10} y} \exp\left[-\frac{(x_a-\eta_A)^2}{2\sigma_A^2}\right] Q\left(\frac{\eta_B-x_a}{\sigma_B}\right) dx_a. \quad (50)$$

Substituting (47) and (50) into (46) and then differentiating with respect to y, we can obtain the following PDF:

$$f_{Y_A|Y_A>Y_B}(y) = \frac{dF_{Y_A|Y_A>Y_B}(y)}{dy} = \frac{Q\left(\frac{\mu_B-10\log_{10} y}{\sigma_B}\right)}{Q\left(\frac{\eta_B-\eta_A}{\sigma}\right)} \frac{\xi}{\sqrt{2\pi}\sigma_A y} \exp\left[-\frac{(10\log_{10} y-\eta_A)^2}{2\sigma_A^2}\right] \quad (51)$$

where $\xi=10/\ln 10$. Finally, the conditional mean is given by

$$E[Y_A|Y_A>Y_B] = \int_0^{\infty} y f_{Y_A|Y_A>Y_B}(y)dy. \quad (52)$$

By substituting (51) into (52) and then letting $z=(10\log_{10} y-\eta_B)/\sqrt{2}\sigma_B$, the conditional mean expression, after some manipulations, is simplified as

$$E[Y_A|Y_A>Y_B] = \frac{a}{\sqrt{\pi}} \frac{\exp\left(\frac{\eta_A}{\xi}+\frac{\sigma_A^2}{2\xi^2}\right)}{Q\left(\frac{\eta_B-\eta_A}{\sigma}\right)} \times \int_{-\infty}^{\infty} \exp\left[-a^2(z+b)^2\right] Q(-\sqrt{2}z)\mathrm{d}z \quad (53)$$

where $a=\sigma_B/\sigma_A$ and $b=(\eta_B-\eta_A-\sigma_A^2/\xi)/\sqrt{2}\sigma_B$. With the help of the following identity [17]:

$$\int_{-\infty}^{\infty} \exp\left[-a^2(z+b)^2\right] Q(-\sqrt{2}z)dz = \frac{\sqrt{\pi}}{a} Q\left(\frac{\sqrt{2}ab}{\sqrt{1+a^2}}\right) \quad (54)$$

we can obtain the conditional mean of Y_A under $Y_A>Y_B$ in a closed-form result

$$E[Y_A|Y_A>Y_B] = \exp\left(\frac{\eta_A}{\xi}+\frac{\sigma_A^2}{2\xi^2}\right) \cdot Q\left(\frac{\eta_B-\eta_A-\sigma_A^2/\xi}{\sigma}\right) \Big/ Q\left(\frac{\eta_B-\eta_A}{\sigma}\right). \quad (55)$$

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