An Adjustable Scheduling Algorithm for Multi-User MIMO Systems

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SUMMARY Multiple Input Multiple Output (MIMO) represents a highly promising technique for 4G communication networks as it uses multiple antennas at the transmitter and receiver to improve the reliability of transmissions and to provide a high data rate. This paper introduces an adjustable scheduling algorithm for multi-user MIMO systems that can provide an advantageous trade-off solution between throughput maximization and fair resource allocation among users. Specifically, our algorithm is proposed as a solution to system requirement issues through the flexible control of fairness factors.

key words: MIMO downlink system, adjustable scheduling algorithm, trade-off solution

1. Introduction

Many types of techniques are available in wireless communication networks. The multiple-input multiple-output (MIMO) technique is one of the most promising techniques available in 4G wireless communication networks. This system uses multiple antennas at the transmitter and receiver to achieve high spectral efficiency without further stress on the frequency bands [1], [2].

In the single user case, MIMO systems improve the transmission reliability through spatial diversity and provide a high data rate through spatial multiplexing. Spatial multiplexing is a technique that increases the data rates at which data streams are split into many sub-streams [3], [4]. It allows the transmission of each sub-stream through multiple antennas separately. Spatial diversity is a technique that enhances the transmission reliability when the same data stream is transmitted through multiple antennas simultaneously [5], [6].

Currently, extended MIMO systems, also known as multi-user MIMO, is an area of research that is more popular than single-user MIMO systems, as this type of system can increase the system capacity significantly through multi-user diversity. Multi-user diversity is a technique of maximizing system capacity through what can be considered a rich scattering environment that provides independent transmission paths from each transmit antenna to each receive antenna. This particular form of diversity can be exploited by tracking the channel fluctuations between each user and the base station, and scheduling transmissions to a user when the relevant instantaneous channel quality is near its maximum value [7].

Many studies related to scheduling in downlink multi-user MIMO systems have been conducted. Essentially, there are three goals of these scheduling schemes in MIMO systems: maximize the system throughput, provide fairness among users, and provide a trade-off solution between the throughput maximization and fairness among users. In 1995, Knopp and Humbelt [8] proposed an opportunistic scheduling algorithm (greedy scheduling) that was able to maximize system throughput through multi-user diversity. This scheduling technique has the user in the best channel state take all resources in an effort to improve the total system throughput. However, this algorithm does not address the clear fairness issues associated with it. In contrast, the round-robin scheduling (RRS) scheme provides strict slot fairness among users but causes considerable degradation of system performance as it assigns antennas to users regardless of the channel state of each user. In 2003, Shin and Lee [9] suggested what they termed the antenna-assisted round-robin scheduling (AA-RRS) scheme, which considers both system efficiency and fairness. However, this scheme cannot use system resources efficiently as scheduled user groups (SUG) are assigned to antennas in a cyclic fashion regardless of the channel state. Therefore, the present study proposes a more efficient scheduling algorithm that posits a trade-off solution between throughput maximization and fair resource allocation among users in terms of system performance management.

2. System Description & Background

2.1 System Description

In this paper, the downlink of a single cell multi-user MIMO cellular system with \( N_T \) transmit antennas and \( N_{R SF}(\geq N_T) \) receive antennas is considered [9], as depicted in Fig. 1. We note that the receiver complexity is a major constraint and requires \( N_R \geq N_T \) in practice [9], [10]. In addition, it is assumed that a base station serves \( K \) users in a time division fashion and that users are distributed uniformly over
a cell area with radius $R$. At the transmitter, the transmit power is equally divided into transmit antennas, and each user has infinite data queues. Each receiver estimates the post-detection signal-to-interference-plus-noise ratio (PD-SINR) for each transmit antenna and feeds the information back to the base station, as shown in Fig. 1. The receiver of each user estimates transmit symbols destined for the user using a linear minimum mean square error (LMMSE) based detector. The optimal joint detection and decoding in the rich scattering environment would require the use of a maximum likelihood (ML) algorithm [11]. However, the computational complexity of optimal ML decoding is beyond the limit of most systems, and, thus, such an approach is not feasible [12]. A suboptimal approach is to use separate suboptimal solution steps for detection and decoding, such as zero forcing (ZF) and minimum mean square error (MMSE) criterion based methods [2]. Although maximum likelihood (ML) receivers have superior performance, linear receivers offer a significant computational reduction. For this reason, a LMMSE based detector is considered in this paper.

2.2 Channel Model

In a MIMO system with $N_T$ transmit antennas and $N_R$ receive antennas, the received signal can be described as

$$ y = Hx + n, \quad (1) $$

where $x$ represents the $N_T \times 1$ vectors of the transmitted symbols, $y$ denotes the $N_R \times 1$ vectors of the received symbols, and $H$ is the $N_R \times N_T$ channel fading coefficients matrix. The element $h_{ij}$ of $H$ represents the fading coefficient between the receive antenna $i$ and the transmit antenna $j$. It was assumed that the channel is fixed during a time slot and each time slot varies independently. Also it is assumed that the coefficients of the channel matrix are i.i.d. (independent, identically distributed) and channel realizations are i.i.d. from frame to frame [4]. Additionally, it was assumed that transmit data signals experience path loss, log normal shadowing, and multi-path fading. With these assumptions, the channel matrix $H_k(t)$ for a user $k$ in time slot $t$ can be expressed as

$$ H_k(t) = \sqrt{SNR_0} \left( \frac{r_k}{R} \right)^{\alpha} \cdot 10^{\frac{S_k(t)}{10}} \cdot G_k(t), \quad (2) $$

where $SNR_0$ denotes the median signal-to-noise ratio (SNR) at the cell boundary, $r_k$ is the distance between the base station and the user $k$, $\alpha$ is the pass loss exponent, and $S_k(t)$ is coefficient of a real Gaussian random process with a zero mean and variance denoted by $\sigma_0^2$. The matrix $G_k(t)$ is a $N_R \times N_T$. And it represents a complex Gaussian random process with a zero mean and unit variance whose element can be expressed as

$$ g_{ij}(t) = \text{Normal}(0, 1/\sqrt{2}) + \sqrt{-1} \cdot \text{Normal}(0, 1/\sqrt{2}), \quad (3) $$

Additionally, $n$ represents the $N_R \times 1$ additive white gaussian noise (AWGN) vectors. It is assumed that a system has a deterministic channel matrix; hence, perfect channel state information (CSI) can be delivered to a base station from each user mobile.

2.3 Capacity of MIMO System

The system capacity of a multi-user MIMO system at time slot $t$ can be described as

$$ C(t) = \sum_{n=1}^{N_T} \log_2(1 + \gamma_{k,n}(t)) \quad (4) $$

The PD-SINR for the channel corresponding to the $n$th transmit antenna and the $k$th user, $\gamma_{k,n}(t)$ can defined as

$$ \gamma_{k,n}(t) = \frac{P_T \cdot \left| W_k(t) \cdot H_k(t) \right|^2}{\sigma_N^2 \cdot N_T \cdot \sum_{m=1}^{N_T} \left| W_k(t) \right|^2 + P_T \cdot \sum_{m=1}^{N_T} \left| W_k(t) \cdot H_k(t) \right|^2}, \quad (5) $$

where $P_T$ is the total transmitted signal power, $\sigma_N^2$ is the noise power per receive antenna, and the MMSE weight matrix $W_k(t)$ is given as

$$ W_k(t) = H_k^H(t) \left( H_k(t) \cdot H_k^H(t) + \left( \frac{\sigma_N^2 \cdot N_T}{P_T} \right) \cdot I_{N_k} \right)^{-1}, \quad (6) $$

where $(\cdot)^H$ denotes the conjugate transpose, and $I_{N_k}$ is the $N_R \times N_R$ identity matrix.

3. Pseudo-SINR Penalty Scheduling Algorithm

The previously developed antenna-assisted round-robin scheduling (AA-RRS) scheme provides fair antenna access to users as a RRS scheme that utilizes what is termed as...
scheduled user group (SUG). However, this scheme increases the system capacity through the use of multiple antennas when achieving a multi-user diversity effect with several users in the SUG [9]. AA-RRS scheduling scheme does not take advantage of the multi-user diversity effects perfectly, as the AA-RRS algorithm selects the users for an SUG in an inefficient round-robin fashion that does not take into account the channel state of each user. Moreover, this algorithm does not adjust the system performance in various situations because the size of the SUG is set to the number of transmit antennas. In addition, this algorithm restricts each scheduled user to the use of only one transmit antenna, which causes degradation of system capacity [9].

In this paper, to make up for the weak points of the AA-RRS, a Pseudo-SINR Penalty Scheduling algorithm (PSPS) is suggested. PSPS is an adjustable scheduling algorithm that satisfies various system requirements that provides a trade-off solution between throughput maximization and fair resource allocation among users through the use of an adjustable fairness factor $\alpha$ in this paper. In previous works, the similar channel aware adaptive control schemes are already applied for the commercial systems such as 802.11a [13]–[15]. PSPS algorithm allows one user who has a better channel condition than any other users to use several antennas at each time slot. Thus, this algorithm can take advantage of multi-user diversity more efficiently than the AA-RRS. The procedure of a PSPS algorithm can be described as follows:

**Step 1) Initial antenna allocation**

In the first time slot $t$, the scheduler assigns each transmit antenna to the user in the best channel condition through the received PD-SINR (post-detection signal-to-interference-plus-noise ratio) matrix. Figure 2 shows an example of the initial antenna allocation that uses the PD-SINR matrix. The element of the PD-SINR matrix represents the post detected SINR (dB) value between each user and each transmit antenna of base station. This channel information is obtained by the feedback operation, as shown in Fig. 1. In this example, if the value of the each element is given like this, base station allocates each transmit antenna to the user(s) in the best channel condition for initial antenna allocation. In this case, the first, fourth, and sixth transmit antennas are allocated to user 1, the second transmit antenna is allocated to user 6, the third transmit antenna is allocated to user 3, and the fifth transmit antenna is allocated to user 4.

**Step 2) Updating PD-SINR matrix**

In the next time slot $t+1$, the scheduler assigns each transmit antenna to the user by use of the P-SINR (Pseudo-SINR) matrix. The P-SINR matrix is an updated PD-SINR matrix that takes into account fairness among users. The updating rule of the P-SINR can be expressed as follows:

i) If user $k$ got transmit antenna(s) at time slot $t$

$$PSINR_{k,u}(t+1) = SINR_{k,u}(t+1) - \omega(t+1) \cdot \sqrt{\alpha(t)} \cdot \sigma$$  \hspace{0.5cm} (7)

ii) Otherwise

$$PSINR_{k,u}(t+1) = SINR_{k,u}(t+1) - \omega(t+1) \cdot \sqrt{\alpha(t)} \cdot \sigma$$  \hspace{0.5cm} (8)

Here, $PSINR_{k,u}(t+1)$ is the element of the P-SINR matrix that represents the P-SINR (dB) value between the $k$th user and the $n$th transmit antenna at time slot $t+1$. Additionally, $SINR_{k,u}(t+1)$ is the element of the PD-SINR matrix that represents the SINR (dB) value between the $k$th user and $n$th transmit antenna at time slot $t+1$. The parameter $\sigma(t)$ denotes the number of transmit antennas assigned to the $k$th user at time slot $t$. And $\omega(t)$ denotes the number of time slots when the $k$th user is not assigned any transmit antennas consecutively until time slot $t$. Hence, $\omega(t)$ can be expressed as

i) If user $k$ didn’t assigned a transmit antenna at time slot $t$

$$\omega(t) = \omega(t-1) + 1$$  \hspace{0.5cm} (9)

ii) If user $k$ assigned transmit antenna(s) at time slot $t$

$$\omega(t) = 0$$  \hspace{0.5cm} (10)

Additionally, $\alpha$ is a adjustable fairness factor with a range of 0 to 1, and $\omega(t+1)$ is a scaling factor that can be described as

$$\omega(t+1) = \frac{\sum_{k=1}^{K} \sum_{n=1}^{N_T} SINR_{k,u}(t+1)}{K \cdot N_T} + \tau \cdot \sigma_{SINR(t+1)}$$  \hspace{0.5cm} (11)

where $\sigma_{SINR(t+1)}$ is the standard deviation of $SINR_{k,u}(t+1)$. And $\tau$ is an experimental scaling factor. The $\omega(t+1)$ value gives the fairness factor $\alpha$ which is the capability of updating the pseudo SINR matrix.

From (7), a penalty is given to users when they are assigned one or more transmit antennas, and compensation is given to users who are not assigned one or more transmit antennas. Thus, if the system administrator wants to provide fairer resource allocation to each user, he or she would have to adjust the fairness factor $\alpha$ to a higher value like 0.9. In addition, if the system administrator wants to provide more efficient system utilization, the fairness factor $\alpha$ should be adjusted to a lower value, like 0.1.
4. Simulation & Result

The proposed PSPS and other scheduling methods (RRS, AA-RRS, Greedy scheduling) were simulated in a downlink multi-user MIMO system, and the performance in terms of throughput and fairness were evaluated when using these algorithms. In this simulation, a 5 × 5 MIMO system in which the system serves 12 users in a time division fashion is assumed. In addition, the 12 users are considered to be distributed uniformly over the cell area with a radius of \( R = 1 \) km. Also assumed was that each user has infinite data queues and that the perfect CSI (Channel State Information) of all users is given to the scheduler of the base station. The transmit signals experience path loss, lognormal shadowing, and multi-path fading. The channel is assumed to be fixed during a time slot and assumed to vary independently over each time slot. The channel matrix \( H_k(t) \) was shown in (2), and all related parameter values are shown in Table 1. Also shown was \( \gamma_k, n(t) \) and \( W_k(t), \omega(t + 1) \) in (5), (6), (11), and all related parameter values are given in Table 2.

In order to evaluate the performance of the proposed PSPS method, the downlink multi-user MIMO system was simulated using MATLAB 6.0. Each scheduling method was simulated with 10,000 timeslots, and the proposed PSPS was compared with other algorithms in terms of throughput performance and fairness among users while varying the fairness factors.

The system throughput of proposed PSPS algorithm was compared with those of other scheduling algorithms (RRS, AA-RRS, Greedy scheduling) by varying the fairness factor \( \alpha \) from 0 to 1. The system throughput of PSPS algorithm is calculated from (4). We assumed spread-spectrum transmissions and that all users share common frequency bands, because space allows multiple transmissions on the same frequency to be possible using multiple radios in a geographic area, in a real multi-point radio system. The results are shown in Figs. 3 and 4. The figures show that the proposed PSPS algorithm has better throughput than the AA-RRS with a fairness factor of \( 0 \leq \alpha \leq 1 \). Moreover, according to the results, the AA-RRS scheme does not improve the system throughput as much as the proposed algorithm as the AA-RRS only exploits very restricted multi-user diversity by use of the SUG, which is determined without any considering the channel condition of each user. In Fig. 4, we compared the throughput between PSPS and other scheduling schemes with different numbers of users by varying fairness factor \( \alpha \) from 0 to 1. This figure shows robust throughput adjusting capability of the PSPS algorithm against the number of users.

The fairness of the proposed PSPS algorithm was compared to that in other scheduling algorithms (RRS, AA-RRS, Greedy scheduling) by varying the fairness factor from 0 to 1. The results are shown in Figs. 5 and 6. To compare the degree of fairness, Jain’s fairness index was used [16]. Jain’s fairness index is defined as

\[
\bar{f}(x_1, x_2, ..., x_n) = \left( \frac{n}{\sum_{i=1}^{n} x_i} \right)^2 \cdot \frac{n}{\sum_{i=1}^{n} x_i^2},
\]

(12)

![Fig. 3](image3.png)  
**Fig. 3** Throughput comparison with other scheduling schemes. \((K = 12\) and \(N_T = 5\))

![Fig. 4](image4.png)  
**Fig. 4** Throughput comparison with other scheduling schemes for different numbers of users and \(N_T = 5\).
These simulation results indicate that the proposed PSPS is able to adjust the throughput fairness to meet the system requirements. Referring to Fig. 5, for a fairness factor of $\alpha = 0$, the PSPS algorithm shows fairness performance that is identical to that of the greedy scheduling algorithm. However, as the fairness factor $\alpha$ increases, the proposed algorithm can approximate the fairness of both the AA-RRS and the RRS schemes. Also Fig. 6 shows robust throughput fairness adjusting capability of PSPS algorithm against the number of users.

The results of this study show that the proposed PSPS algorithm always provides better throughput fairness compared to the greedy scheduling algorithm when the fairness factor $\alpha$ is adjusted from 0 to 1. Additionally, the proposed algorithm provides a reasonable throughput fairness enhancement when the fairness factor $\alpha$ is increased from 0 to 1. In the results of throughput and fairness comparisons with other algorithms, it was found that the proposed PSPS provides performance that is superior to the RRS and AA-RRS algorithms in terms of throughput maximization. Moreover, it guarantees an adjustable fairness among users.

5. Conclusions

An adjustable scheduling algorithm for downlink multi-user MIMO systems is proposed in this study. It allows advantageous trade-off solutions between throughput maximization and fairness among users by adjusting the fairness factor depending on the system requirements. The proposed algorithm is a method that is adaptable to various system requirements in which the algorithm can compensate poor channel users who are seldom allocated transmit antennas and penalize greedy users who monopolize the transmit antennas via control of the fairness factor $\alpha$ in the range of 0 to 1.

From the simulation results, the proposed PSPS algorithm permits a trade-off solution that guarantees a minimum resource allocation to each user and provides additional access chance to users with better channel conditions relative to other users in an effort to enhance the overall system throughput by adjusting the fairness factors. Moreover, the PSPS algorithm shows different performances with various fairness factors. It shows system performance similar to that of greedy scheduling algorithms when the fairness factor is given as $\alpha = 0$, and it shows system performance that is nearly identical to that of the RRS or AA-RRS algorithm when the fairness factor is given as $\alpha = 1$. The proposed PSPS algorithm was also found to provide consistently better throughput fairness compared to the greedy scheduling algorithm with any fairness factor $\alpha$ with a range of 0 to 1.

It is anticipated that future work will investigate the utilization of our proposed algorithm with the other MIMO signal detectors (ML, ZF and EMT). In this paper, our current algorithm has been customized to LMMSE detector. However, it would be desirable to extend our algorithm for the other sophisticated detectors.

References


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