An Adaptive User Scheduling Algorithm for 6G Massive MIMO Systems

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Abstract*—Massive MIMO (Multiple-Input Multiple-Output) is a promising wireless access technology that has emerged as a solution to the ever-increasing demand for network capacity. Massive MIMO is expected to play a crucial role in the deployment of 5G and upcoming 6G networks, enabling the realization of their full potential capacity. Despite the numerous benefits, user scheduling during downlink communication in Massive MIMO systems is a challenging task due to the large number of antenna terminals. In this paper, we propose a novel scheduling algorithm aimed at improving the area throughput, sum capacity, error performance, and ensuring fairness among all users. The proposed algorithm uses the average channel rate as the scheduling criteria, which is calculated from the channel state information obtained from the users during uplink transmission. To evaluate the performance of our proposed algorithm, we conducted simulations using Matlab. Our results demonstrate that our proposed channel rate-based scheduling algorithm is superior to conventional scheduling algorithms in terms of sumrate, throughput, and bit error performance while also ensuring fairness among all users. The proposed algorithm can address the challenge of user scheduling in Massive MIMO systems and contribute to the efficient deployment of 5G and 6G networks. The ability to improve system capacity, area throughput, and provide fairness in communication is of great importance in meeting the high demands of future wireless networks. Our approach could pave the way for further research in improving the performance of Massive MIMO systems, thereby advancing the potential of 5G and 6G networks.

***Index Terms*—5G, 6G, Massive MIMO, User Scheduling**

I. Introduction

THe demand for high data rates has skyrocketed due to the growing usage of mobile devices and the emergence of new applications that require high-speed data transfer. This has led to the development of next-generation wireless systems such as 5G, beyond 5G, and 6G networks, which are expected to provide high data rates, low latency, and better quality of service. Multiple-input Multiple-output (MIMO) technology has been a key factor in the development of previous generation wireless networks such as 3G and 4G, and it is expected to continue playing a critical role in future wireless systems. MIMO technology utilizes multiple antennas at both the transmitter and receiver to create multiple signal paths, which can be used to improve the robustness of the link against fading and interference [1]–[6].

One of the major benefits of MIMO technology is diversity gain, which refers to the improvement in signal quality due to the use of multiple signal paths. By leveraging the spatial dimension, MIMO technology can create multiple independent signal paths between the transmitter and receiver, which can help mitigate the effect of fading on the signal strength. This is particularly useful in environments with a high degree of multipath propagation, such as urban areas. Another key benefit of MIMO technology is multiplexing gain, which refers to the increase in data rate due to the use of multiple signal paths. By sending independent data streams on each signal path, MIMO technology can effectively increase the bandwidth of the link, resulting in higher data rates. This is particularly useful in applications that require high-speed data transfer, such as video streaming, online gaming, and virtual reality.

To cater to more users with better quality of service, the MIMO technique called massive MIMO plays a critical role. Massive MIMO employs hundreds of antennas at the base station, serving multiple users simultaneously. Massive MIMO is a wireless access technology operating below 6GHz, which plays a crucial role in current 5G and upcoming 6G networks by offering high spectral and energy efficiency with

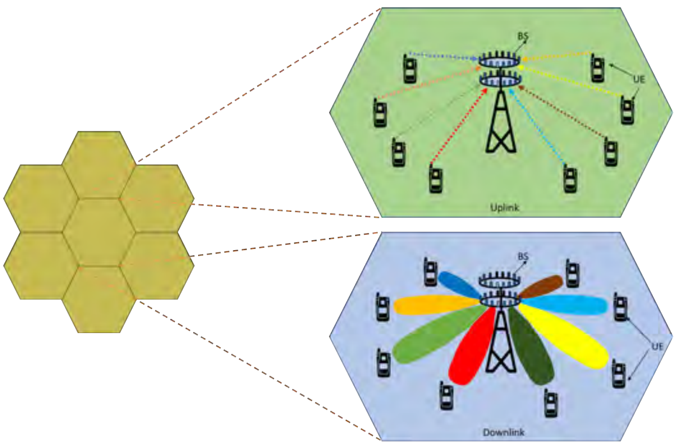

Fig. 1. Massive MIMO uplink and downlink system.

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low latency [9]- [16]. It uses hundreds of antennas at the base station to serve tens of users simultaneously, providing high multiplexing and diversity gains while mitigating fading effects. Massive MIMO is essential to support the increasing demand for high data rates driven by applications such as blockchain, cyber-security, Smart Vehicles, the Internet of Things, augmented reality, virtual reality, and extended reality. The technique uses beamforming to direct signals towards users during the downlink, and the narrower beams resulting from more antennas improve spatial focus. Figure 1 shows a typical massive MIMO system where uplink pilot signals are transmitted by users towards the base station during uplink communication, and the downlink communication uses beamforming to direct signals towards the users. As the number of antennas increases, the beams become narrower, resulting in better spatial focus on users [17], [18].

However, with hundreds of antenna terminals, user scheduling during downlink communication is one of the major challenges in massive MIMO system deployment. A suitable user scheduling method during the downlink is necessary to enhance the throughput of massive MIMO systems when the number of active users is greater than the number of base station antenna terminals. Scheduling users with better channel conditions can improve the total area throughput. However, maintaining an adequate fairness level is equally important to ensure timely scheduling for users with weaker channel conditions. Considerable research has been conducted to develop optimal user scheduling algorithms. Greedy algorithms have been discussed in [19]- [21], which provide better fairness performance but fail to achieve optimal throughput. Traditional algorithms, Round Robin (RR), and Proportional Fair (PF) are better in terms of fairness but do not achieve optimal fairness. Linear methods like Zero Forcing (ZF) and Minimum Mean Square Error (MMSE) have been explored in [22]- [23]. The authors in [24]–[26], [28]–[31] have investigated user scheduling methods for downlink MIMO systems, but optimal performance in terms of both throughput and fairness has not been achieved. In this paper, we propose an adaptive user scheduling algorithm based on channel rate to provide the user with optimal throughput and ensure fairness among all the users.

A. *Contribution of the Paper*

1) The user scheduling issue during the downlink massive MIMO system is investigated
2) An adaptive user scheduling scheme based on instantaneous channel rate is proposed
3) The sum rate, per-user throughput, and error performance of the proposed algorithm are accessed and compared with traditional scheduling algorithms
4) We evaluated the fairness index of the proposed algorithm. We have used Jain's fairness index to compute the fairness index.
5) The results obtained from the Matlab simulations show that the proposed algorithm is fair and performs better than the traditional user scheduling algorithm in terms of sumrate, per-user throughput, and error performance.

B. *Outline*

The remainder of the paper is structured as follows: Section II defines the downlink system model for massive MIMO with M antennas and N users. The proposed adaptive algorithm is described in III. The simulation steps, required parameters, and algorithm analysis are presented in IV. Finally, V concludes the paper by encapsulating the major concepts of the paper.

C. *Notations*

In this paper, there are specific notations and terminologies used to represent various mathematical concepts. Column vectors are denoted by lower-case letters, while matrices are denoted by upper-case letters. The inverse of a matrix is denoted by $(.)^{-1}$, and the transpose is represented by $(.)'$. The hermitian transpose is denoted by $(.)^H$. The circular symmetric complex Gaussian distribution with zero mean and co-variance V is represented by $\mathcal{CN}(0, V)$. The space of M-element complex vectors is denoted by $\mathbb{C}^M$, where M is a positive integer. The $M \times M$ identity matrix is represented by I_M, which is a square matrix with ones on the diagonal and zeros elsewhere.

II. SYSTEM MODEL

In massive MIMO, the BS is equipped with numerous antennas, typically numbering in the hundreds or thousands. Downlink is the data transmission from the base station to the user equipment, such as mobile phones or laptops. The fundamental concept behind massive MIMO is to exploit the large number of antennas at the BS to concurrently communicate with multiple users utilizing the same time-frequency resource. This is accomplished by spatially combining signals from the BS's antennas to create unique signal combinations for each user. Downlink massive MIMO systems capitalize on the numerous antennas at the BS to enhance the quality and capacity of the wireless link to the users. Beamforming methods are employed by the BS to direct the transmitted signal towards each user, increasing the signal-to-noise ratio (SNR) and reducing interference from other users.

A massive MIMO downlink system is considered with M base station antenna terminals and N users. In the course of the downlink communication, the base station will send an independent and autonomous signal to each active user. If U users are waiting for their turn to be scheduled, the base station selects S users ($S <= U$) according to the scheduling algorithm. The base station will apply a precoder before sending the downlink signal towards the user. The primary objective of precoding is to optimize the wireless channel between the base station and the users by modifying the phase and amplitude of the transmitted signal. The purpose of this modification is to reduce interference and enhance the quality of the signal received by the user. Precoding is a process that involves the application of a matrix operation to the data signals transmitted from the base station antennas. This operation is intended to decrease the interference between users and improve the signal-to-noise ratio (SNR) at the receiver's end. Several precoding algorithms are used in Massive MIMO systems, including zero-forcing (ZF) precoding and minimum

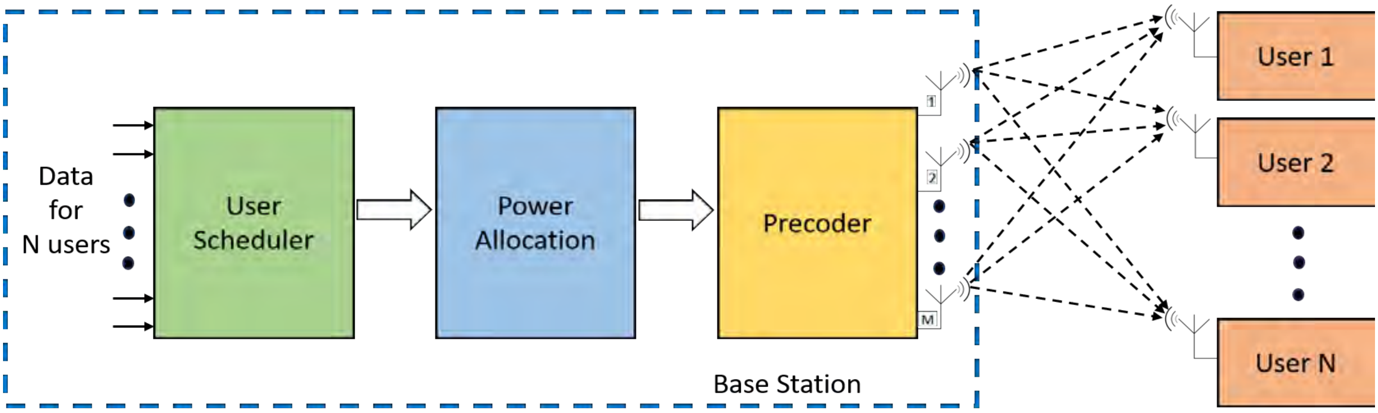

Fig. 2. System Model with M base station antenna serving N users.

mean squared error (MMSE) precoding. The implementation of precoding during user scheduling can lead to increased data rates, better spectral efficiency, and improved overall system performance in terms of signal quality and interference reduction. Therefore, precoding is a critical component in the design and optimization of Massive MIMO systems. The signal received by user i can be represented as:

$$y_i = Hx_i + n_i \tag{1}$$

Where,

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ . \\ . \\ . \\ x_i \end{bmatrix} \quad and \quad H_i = \begin{bmatrix} h^i_{11} & h^i_{12} & . & h^i_{1N} \\ h^i_{21} & h^i_{22} & . & h^i_{2N} \\ . & . & . & . \\ . & . & . & . \\ h^i_{N1} & h^i_{N2} & . & h^i_{NM} \end{bmatrix}$$

y_i is the signal received by the i_{th} user, and x_i is the signal sent towards the user from the base station i. $H \in \mathbb{C}^{N\times M}$ is the channel vector between the user terminals and the base station antenna terminals, where elements of H are independent and identically distributed. n_i is the added white Gaussian noise at the i_{th}.

We do the precoding before scheduling the user to minimize multi-user interference. We get the matrix for precoding by stacking the beamforming vectors and user signals.

$$y_i = HWx_i + n_i \tag{2}$$

Where,

$$W = \begin{bmatrix} p_1 & p_2 & . & . & . & p_j \end{bmatrix}$$

$W \in \mathbb{C}$ is the precoding matrix, which contains a set of precoders. p_j is the vector used for precoding the j_{th} user. For our simulations, we have applied two simple linear precoders, ZF and MMSE [34]:

$$W_{ZF} = H^H(HH^H)^-1 \tag{3}$$

$$W_{MMSE} = H^H(HH^H + \sigma^2 I)^-1 \tag{4}$$

We compute the sumrate by considering the uniform power allocation among each user as [32]:

$$Sumrate = \sum_{i=1}^{N} \log_2\left(1 + \frac{|b_i h_i|^2}{1 + \sum_{j=1, j\neq i}^{N} |b_i h_j|^2}\right) \tag{5}$$

where, b_k is the k_{th} row of precoding matrix B and h_k is the k_{th} row of the channel matrix H.

III. PROPOSED ALGORITHM FOR DOWNLINK USER SCHEDULING

The proposed algorithm is summarized in 1. We initialize the active users set U, including N active users. The set of selected users is S, which is null initially as non of the users are scheduled. Then we calculate the instantaneous channel rate for each user:

$$C_j = log_2\left(1 + \sqrt{\sum_{j=1}^{N} |h_j|^2}\right) \tag{6}$$

The mean channel rate is computed based on the active users waiting to be scheduled. The calculated mean channel rate will also be the selection criteria for the proposed algorithm.

$$\bar{C} = \frac{\sum C_j}{N} \tag{7}$$

The user with an instantaneous channel rate closest to the mean channel rate is selected first. Once the selected user is scheduled, we update the set containing the remaining active and selected users.

$$\pi(j) = argmin|||A_j| \tag{8}$$

$$S = S\,U\,\pi(j) \tag{9}$$

$$U = U - S \tag{10}$$

The process of user selection is repeated until all the active users are scheduled. Then, the mean channel rate is re-evaluated for the next set of active users.

$$U \neq \{\phi\} \tag{11}$$

Algorithm 1 Proposed Algorithm for Massive MIMO Downlink Scheduling

Initialization:
1. $U = \{1, 2, 3, 4, ...N\}$
2. $S = \{\phi\}$
3. $j = 0$

Channel Rate Calculation:

4. $C_j = log_2\left(1 + \sqrt{\sum_{j=1}^{N} |h_j|^2}\right)$
5. $\bar{C} = \frac{\sum C_j}{N}$

Selection Criteria:
6. $A_j = |C_j - \bar{C}|$

Algorithm iteration:
do
7. $\pi(j) = argmin|||A_j|$
8. $S = S\,U\,\pi(j)$
9. $U = U - S$
10. $i = i + 1$

While $U \neq \{\phi\}$

IV. Simulation Results and Analysis

In this section, we analyze the results obtained from the Matlab simulations. For simulations, we set up a massive MIMO base station with many antenna terminals (16 to 512). We assume that all the antenna terminals are communicating with 128 single active users simultaneously. We have considered various antenna configurations with different modulation techniques (QPSK, 16QAM, 16QAM) for conducting the simulations. The system's bandwidth is set to 20 MHz, whereas a carrier frequency of 2.5 GHz is used. A perfect channel state information (CSI) is assumed between the user and the base station, and the Rayleigh fading channel model is used for simulations. We have compared our proposed algorithm with traditional schedulers like Proportional Fair (PF) and Round Robin (RR) algorithms for analysis. In addition, we have used ZF and MMSE precoding to reduce the effect of multi-user interference and to simplify the processing required at the receiver. The simulation parameters used are shown in I.

Fig. 3 depicts the error performance of the proposed algorithm with 16 users, 16 base station antenna terminals, 16QAM modulation, and MMSE precoding. The proposed algorithm exhibits better BER performance than the traditional algorithm across the entire range of user SNR in the simulation. For instance, at a BER of 10^{-2}, the proposed algorithm achieves a 6dB gain over the RR algorithm and a 4dB gain over the PF algorithm. Similarly, conducting the same experiment with 16 users, 16 base station antenna terminals, and MMSE

TABLE I
SIMULATION PARAMETERS

Parameter	**Value**
Base Station Antenna Terminal	16 to 512
Number of Users	128
Carrier Frequency	2.5 GHz
Bandwidth	20 MHz
Coherence Internal	200 Symbols
Channel Model	Uncorrelated Rayleigh Fading
Signal Variance	2
SNR	0 dB - 25dB
Modulation	QPSK, 16QAM, 64QAM

precoding, but with 64QAM modulation, results in degraded error performance for all algorithms, as shown in Fig. 4. At BER 10^{-1}, the proposed algorithm achieves almost 3 dB gain over the PF algorithm and 4dB gain over the RR algorithm. Nonetheless, the per-user throughput increases for all algorithms with higher modulation order. Additionally, the simulation with comparable parameters and QPSK modulation, depicted in Fig. 5, results in improved error performance for all algorithms. This improvement stems from QPSK being less susceptible to interference and noise in comparison to higher modulation orders such as 16QAM and 64QAM used in our experiments.

Fig.6 illustrates the simulation outcomes when 16 users,

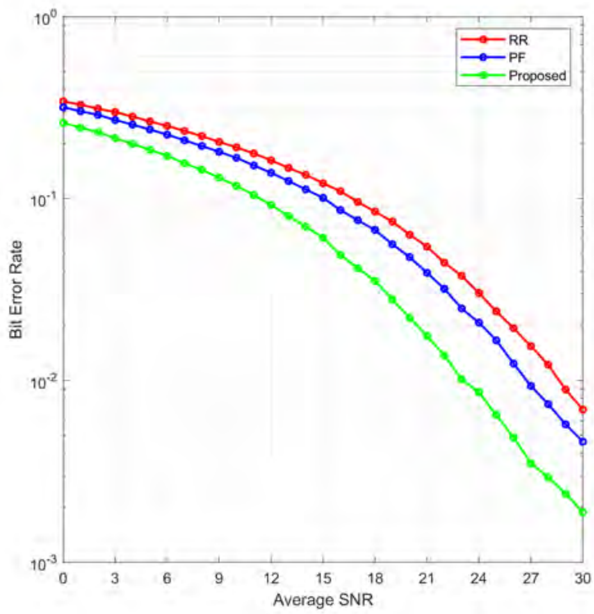

Fig. 3. BER vs. SNR performance with 16 users, 16 base station antennas, 16QAM modulation, and MMSE precoding.

16 base station antenna terminals, and 16QAM modulation are employed, but with Zero Forcing (ZF) precoding. The performance trend follows the same pattern as the previous experiment; however, the overall performance of all algorithms has decreased. Specifically, at a BER of 10^{-1}, the proposed algorithm outperforms the RR algorithm by 5 dB and PF by 3.5 dB, underscoring the superiority of the proposed algorithm's BER performance compared to conventional algorithms. In Fig.7, QPSK modulation is employed, and all algorithms demonstrate enhanced error performance. This improvement can be attributed to the lower susceptibility of lower modulation orders, such as QPSK, to noise and interference. In contrast, higher modulation orders, such as 16QAM, are more susceptible to noise and interference, resulting in degraded error performance.

Fig.8 illustrates the analysis of the sumrate performance of the proposed algorithm. This simulation involved 16 base

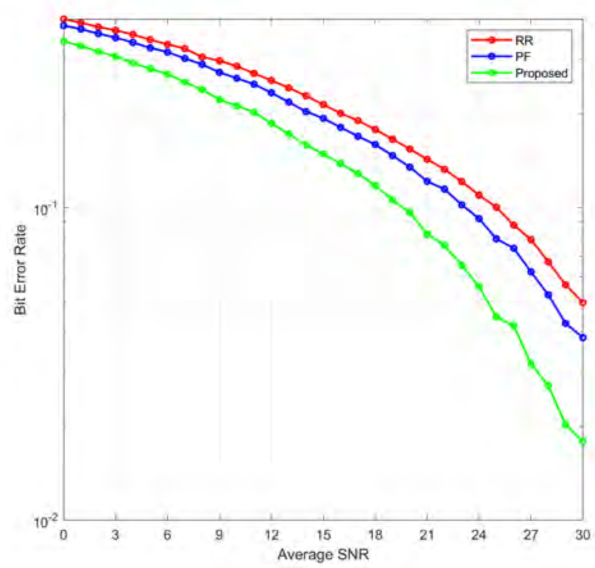

Fig. 4. BER vs. SNR performance with 16 users, 16 base station antennas, 64QAM modulation, and MMSE precoding.

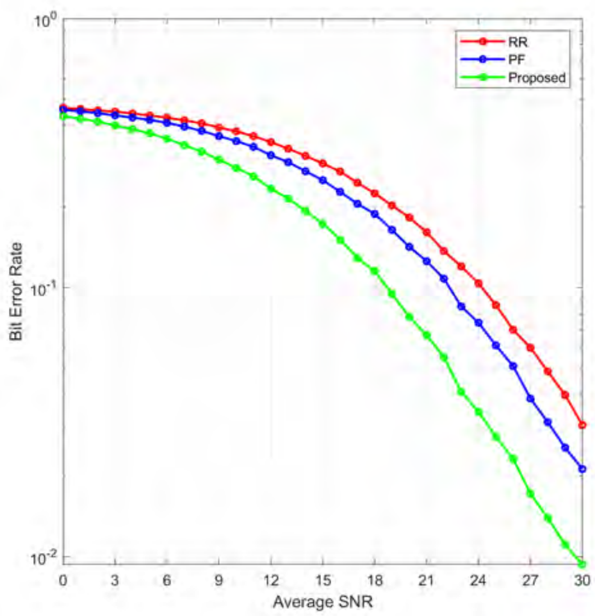

Fig. 6. BER vs. SNR performance with 16 users, 16 base station antennas, 16QAM modulation, and ZF precoding.

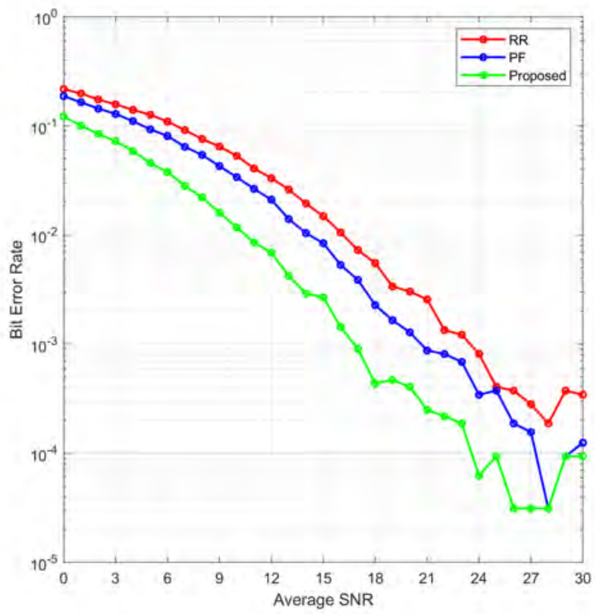

Fig. 5. BER vs. SNR performance with 16 users, 16 base station antennas, QPSK modulation, and MMSE precoding.

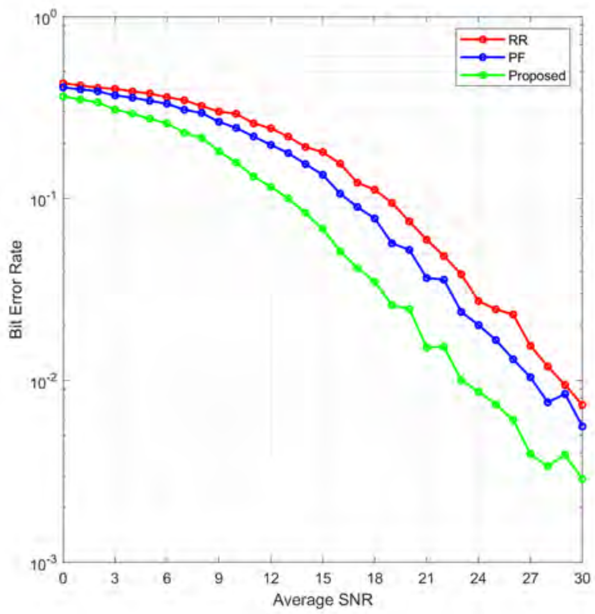

Fig. 7. BER vs. SNR performance with 16 users, 16 base station antennas, QPSK modulation, and ZF precoding.

station antenna terminals communicating with 16 users using 16QAM modulation and MMSE precoding. The simulation results indicate that the proposed algorithm outperforms the traditional algorithms. For instance, at an SNR of 21dB, the proposed algorithm achieves a sum rate of 60 bits/s/Hz, whereas the PF algorithm attains a sum rate of 43 bits/s/Hz, and the RR algorithm exhibits the poorest performance, with a sum rate of 38 bits/s/Hz. The high sum rate is primarily attributed to the increased number of antenna terminals. Nevertheless, as the number of active users in a cell grows, the sum rate will eventually reach a saturation point.

We conducted a similar experiment using ZF precoding, and the sumrate performance was comparable to that of MMSE precoding, as demonstrated in Fig.9. With ZF precoding at an SNR of 21dB, the proposed algorithm attained a sumrate of 60 bits/s/Hz, while the PF and RR algorithms recorded a sum rate of 42 bits/s/Hz and 37 bits/s/Hz, respectively.

We then considered the performance of our proposed algorithm with several modulation techniques. This simulation was administered with 16 base station antenna terminals communicating with 16 users using 16QAM modulation and MMSE precoding. As shown Fig.10, QPSK exhibited the best error performance across a range of SNRs, while 64QAM displayed the best performance due to its ability to transmit more data per symbol. However, higher modulation orders are more susceptible to noise and interference, leading to higher error rates. Therefore, the optimal modulation order depends on the application and the user's requirements. Furthermore, we performed a simulation with ZF precoding using 16 base station antenna terminals communicating with 16 users via 16QAM modulation, as shown in Fig.11. We observed that the performance was nearly identical to that of MMSE precoding.

We evaluated the proposed algorithm's average throughput per user performance. This simulation was administered with 16 base station antenna terminals communicating with 16 users using 16QAM modulation and MMSE precoding. As shown in Fig. 12, the average per-user throughput for the proposed algorithm was best among the compared algorithms. Our algorithm achieved a per-user throughput of 3.14 Mbps, whereas, for RR and PF algorithms, it was found to be 2.33 Mbps and 2.53 Mbps, respectively.

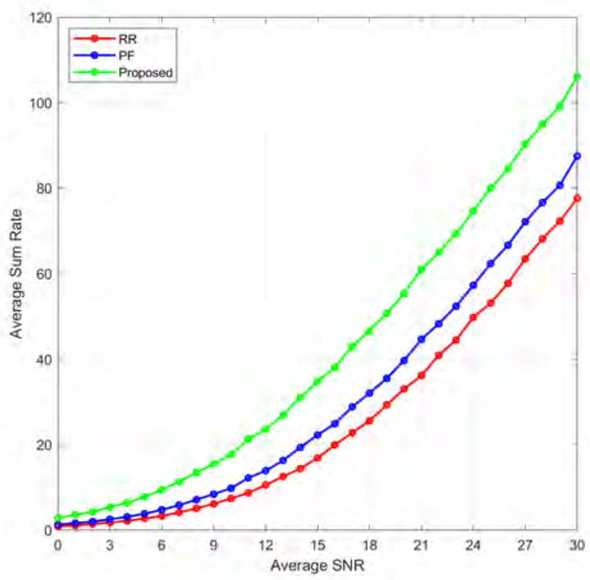

Fig. 9. Sumrate vs. BER performance with 16 users, 16 base station antennas, 16QAM modulation, and ZF precoding.

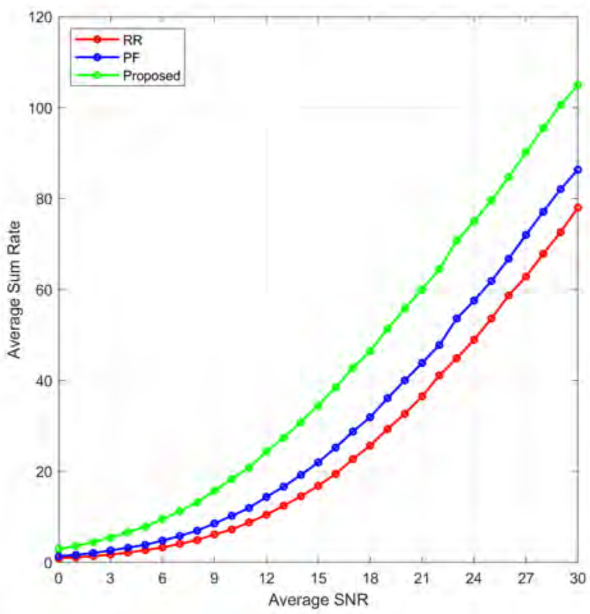

Fig. 8. Sumrate vs. BER performance with 16 users, 16 base station antennas, 16QAM modulation, and MMSE precoding.

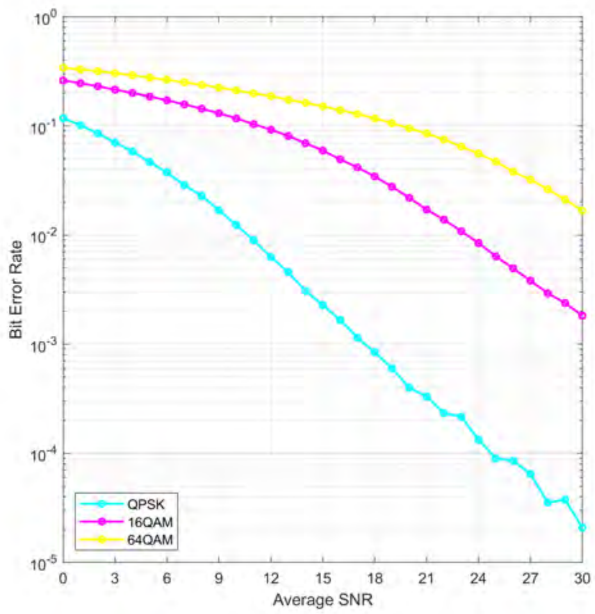

Fig. 10. BER performance of the proposed algorithm with several modulation schemes with 16 users, 16 base station antennas, and MMSE precoding

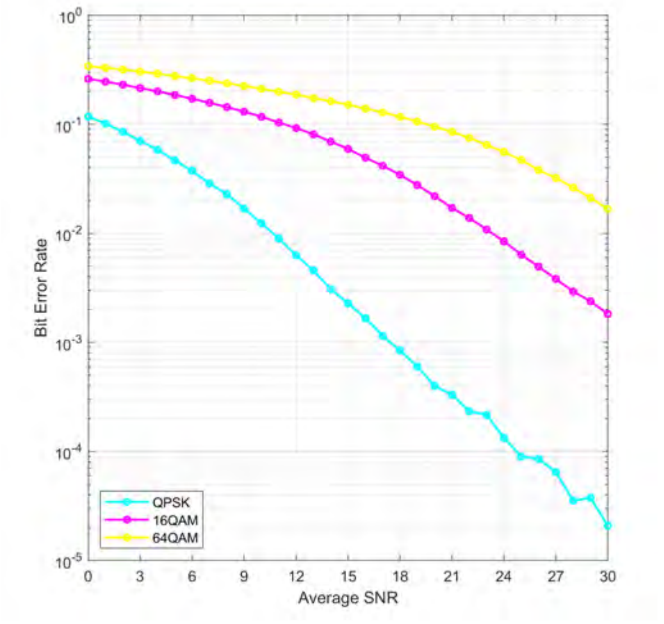

Fig. 11. BER performance of the proposed algorithm with several modulation schemes with 16 users, 16 base station antennas, and ZF precoding

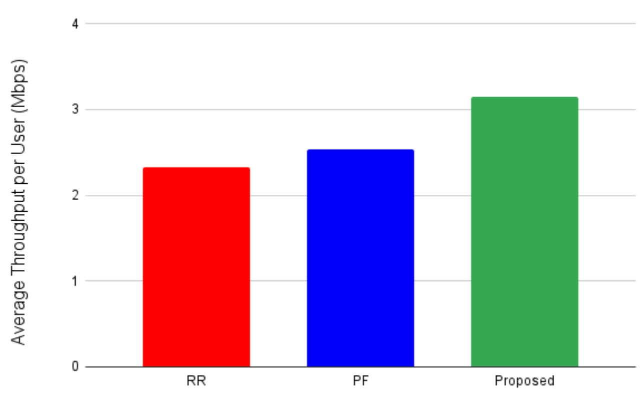

Fig. 12. Average throughput per user with 16 users, 16 base station antennas, 16QAM modulation, and MMSE precoding.

We use Jain's fairness index to evaluate the performance of the proposed algorithm. Jain's fairness index is a widely-used metric for assessing fairness in the distribution of limited resources, especially in the context of networking and telecommunications. This metric is particularly useful when multiple users or applications are competing for a finite amount of resources like CPU time or wireless bandwidth. It offers an objective way of quantifying the degree of fairness in resource allocation and comparing different allocation schemes. The fairness of resource allocation is critical in networking to prevent congestion, service degradation, or even network failure. Jain's fairness index allows for the comparison of resource allocation schemes by measuring how equitably resources are distributed among users or applications. An index value close to 1 suggests that resources are being allocated fairly to all users or applications, whereas a value closer to 0 indicates an unfair distribution, with some users or applications receiving more than their fair share of resources.

We measured Jain's fairness index for all the algorithms [33].

$$\mathcal{F}(X) = \frac{\left(\sum_{i=1}^{N} x_i\right)^2}{\sum_{i=1}^{N} x_i^2} \tag{12}$$

Where $\mathcal{F}$ is the fairness index whose values are between 0 and 11, and x_j is throughput for ith user. As shown in II, simulation results show that the fairness provided by the proposed algorithm is similar to that of the traditional algorithms.

TABLE II
FAIRNESS INDEX COMPARISON

Scheduling Algorithm	**Fairness Index**
Round Robin	0.973
Proportional Fair	0.983
Proposed	0.999

V. CONCLUSION

In conclusion, this paper addressed the issue of user scheduling during downlink signaling in a massive MIMO system. The proposed algorithm takes into account the instantaneous channel rate, which enables it to adaptively schedule users based on their current channel conditions. This results in a significant improvement in the sum rate and per-user throughput, as well as providing better error performance and fairness among all users. The simulation results also showed that the performance of the proposed algorithm varied with different modulation techniques. Specifically, 64QAM provided the best data rate, while QPSK provided the best error rate. This indicates that the choice of modulation technique can significantly affect the performance of the user scheduling algorithm, and it is essential to choose an appropriate modulation technique that suits the requirements of the system.

Furthermore, the fairness of the proposed algorithm was assessed using Jain's fairness index, which is a commonly used metric for measuring fairness in communication systems. The fairness index of 0.99 obtained from the proposed algorithm indicates that the algorithm ensures fairness among all users, which is an essential requirement for any scheduling algorithm. The proposed adaptive user scheduling algorithm based on instantaneous channel rate is a suitable candidate for downlink user scheduling in a massive MIMO system with a large number of antennas. The algorithm provides improved performance in terms of sum rate, per-user throughput, error performance, and fairness, and can be adapted to different modulation techniques to suit the requirements of the system.

REFERENCES

[1] M. Giordani, M. Polese, M. Mezzavilla, S. Rangan, and M. Zorzi, "Toward 6G Networks: Use Cases and Technologies," *IEEE Commun. Mag.*, vol. 58, pp. 55-61, 2020.

[2] A. Kurve, "Multi-user MIMO systems: The future in the making," *IEEE Potentials*, vol. 28, pp. 37-42, 2009.

[3] G. J. Foschini and M. J. Gans, "On Limits of Wireless Communications in a Fading Environment When Using Multiple Antennas," *Wireless Pers. Commun.*, vol. 6, pp. 311-335, 1998.

[4] Q. H. Spencer, C. B. Peel, A. L. Swindlehurst, and M. Haardt, "An introduction to the multi-user MIMO downlink," *IEEE Commun. Mag.*, vol. 42, pp. 60-67, 2004.

[5] A. Paulraj and T. Kailath, "Increasing Capacity in Wireless Broadcast Systems Using Distributed Transmission/Directional Reception (DTDR)," U.S. Patent 5,345,599, Sep. 6, 1994.

[6] D. Nojima, L. Lanante, Y. Nagao, M. Kurosaki, and H. Ochi, "Performance evaluation for multi-user MIMO IEEE 802.11ac wireless LAN system," in *Proceedings of the 2012 14th International Conference on Advanced Communication Technology (ICACT)*, PyeongChang, Korea, Feb. 19-22, 2012, pp. 804–808.

[7] A. Paulraj, R. Nabar, and D. Gore, *Introduction to Space-Time Wireless Communications*. New York, USA: Cambridge University Press, 2008.

[8] IEEE Draft Standard Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) specifications: Amendment 4: Enhancements for Higher Throughput. P802.11n D3.00, Sept. 2007.

[9] 3rd Generation Partnership Project; Technical Specification Group Radio Access Network; Evolved Universal Terrestrial Radio Access (EUTRA); Multiplexing and channel coding (Release 9). 3GPP Organizational Partners TS 36.212 Rev. 8.3.0, May 2008.

[10] J. Hoydis, K. Hosseini, S. Ten Brink, and M. Debbah, "Making smart use of excess antennas: Massive MIMO, small cells, and TDD," *Bell Labs Technical Journal*, vol. 18, no. 2, pp. 5-21, Sep. 2013.

[11] R. Chataut and R. Akl, "Optimal pilot reuse factor based on user environments in 5G Massive MIMO," *2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC)*, Las Vegas, NV, 2018, pp. 845-851.

[12] R. Chataut, R. Akl and U. K. Dey, "Least Square Regressor Selection-Based Detection for Uplink 5G Massive MIMO Systems," *2019 IEEE 20th Wireless and Microwave Technology Conference (WAMICON)*, Cocoa Beach, FL, USA, 2019, pp. 1-6.

[13] T. L. Marzetta, "Noncooperative cellular wireless with unlimited numbers of base station antennas," *Wireless Communications, IEEE Transactions on*, vol. 9, no. 11, pp. 3590-3600, 2010.

[14] E. G. Larsson, F. Tufvesson, O. Edfors, and T. L. Marzetta, "Massive MIMO for Next Generation Wireless Systems," *IEEE Commun. Mag.*, vol. 52, no. 2, pp. 186-195, Feb. 2014.

[15] F. Rusek, D. Persson, B. K. Lau, E. G. Larsson, T. L. Marzetta, O. Edfors, and F. Tufvesson, "Scaling up MIMO: Opportunities and Challenges with Very Large Arrays," *IEEE Signal Process. Mag.*, vol. 30, no. 1, pp. 40-60, Jan. 2013.

[16] T. L. Marzetta, "Massive MIMO: An Introduction," in *Bell Labs Technical Journal*, vol. 20, pp. 11-22, 2015.

[17] R. Chataut and R. Akl, "Massive MIMO Systems for 5G and beyond Networks—Overview, Recent Trends, Challenges, and Future Research Direction," *Sensors*, vol. 20, no. 10, p. 2753, 2020.

[18] R. Chataut, R. Akl, U. K. Dey, and M. Robaei, "SSOR Preconditioned Gauss-Seidel Detection and Its Hardware Architecture for 5G and beyond Massive MIMO Networks," *Electronics*, vol. 10, no. 5, p. 578, 2021.

[19] G. Dimic and N. D. Sidiropoulos, "On downlink beamforming with greedy user selection: performance analysis and a simple new algorithm," *IEEE Transactions on Signal Processing*, vol. 53, no. 10, pp. 3857-3868, Oct. 2005.

[20] J. Wang, D. J. Love, and M. D. Zoltowski, "User selection with zero-forcing beamforming achieves the asymptotically optimal sum rate," *IEEE Transactions on Signal Processing*, vol. 56, no. 8, pp. 3713-3726, Aug. 2008.

[21] M. Kobayashi and G. Caire, "Joint beamforming and scheduling for a multi-antenna downlink with imperfect transmitter channel knowledge," *IEEE Journal on Selected Areas in Communications*, vol. 25, no. 7, pp. 1468-1477, Sep. 2007.

[22] K. Lyu, "Capacity of multi-user MIMO systems with MMSE and ZF precoding," in *2016 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, San Francisco, CA, 2016, pp. 1083-1084.

[23] D. L. Colon, F. H. Gregorio, and J. Cousseau, "Linear precoding in multi-user massive MIMO systems with imperfect channel state information," in *2015 XVI Workshop on Information Processing and Control (RPIC)*, Cordoba, 2015, pp. 1-6.

[24] M. Sharif and B. Hassibi, "On the capacity of MIMO broadcast channels with partial side information," *IEEE Trans. Inf. Theory*, vol. 51, no. 2, pp. 506–522, Feb. 2005.

[25] T. Al-Naffouri, M. Sharif and B. Hassibi, "How much does transmit correlation affect the sum-rate scaling of MIMO Gaussian broadcast channels?," *IEEE Trans. Commun.*, vol. 57, no. 2, pp. 562–572, Feb. 2009.

[26] T. Yoo and A. Goldsmith, "On the optimality of multi-antenna broadcast scheduling using zero-forcing beamforming," *IEEE J. Sel. Areas Commun.*, vol. 24, no. 3, pp. 528–541, Mar. 2006.

[27] H. Yang, "User Scheduling in Massive MIMO," in *Proceedings of the 2018 IEEE 19th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, Kalamata, Greece, 25–28 June 2018, pp. 1–5.

[28] S. Huang, H. Yin, J. Wu, and V.C.M. Leung, "User selection for multi-user MIMO downlink with zero-forcing beamforming," *IEEE Trans. Veh. Technol.*, vol. 62, pp. 3084–3097, Sept. 2013.

[29] Y. Cai, J. Yu, Y. Xu, and M. Cai, "A comparison of packet scheduling algorithms for OFDMA systems," in *Proceedings of the 2008 2nd International Conference on Signal Processing and Communication Systems*, Gold Coast, QLD, Australia, 15–17 Dec. 2008, pp. 1–5.

[30] M.F. Hamdi, R.A. Saeed, and A. Abbas, "Downlink scheduling in 5G massive MIMO," *J. Eng. Appl. Sci.*, vol. 13, pp. 1376–1381, Apr. 2018.

[31] K. Djouani, G. Maina, M. Mzyece, and G. Muriithi, "A low complexity greedy scheduler for multiuser MIMO downlink," in *Proceedings of the Southern African Telecommunications Networks and Applications Conference (SATNAC)*, Port Edward, South Africa, 5–8 Sept. 2010.

[32] R. Chataut and R. Akl, "Channel Gain Based User Scheduling for 5G Massive MIMO Systems," in *2019 IEEE 16th International Conference on Smart Cities: Improving Quality of Life Using ICT and IoT, and AI (HONET-ICT)*, Charlotte, NC, USA, 2019, pp. 049-053.

[33] R. Jain, D. Chiu, and W. Hawe, "A Quantitative Measure of Fairness and Discrimination for Resource Allocation in Shared Systems, Digital Equipment Corporation," *Technical Report DEC-TR-301*, Tech. Rep., 1984.

[34] R. Akl, "An Efficient and Fair Scheduling for Downlink 5G Massive MIMO Systems," in *11th IEEE Texas Symposium on Wireless and Microwave Circuits and Systems (TSWMCS 2020)*, May 2020.

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