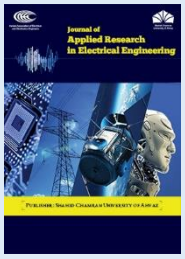
Shahid Chamran University of Ahvaz

Iranian Association of Electrical and Electronics Engineers

Journal of Applied Research in Electrical Engineering

E-ISSN: 2783-2864
P-ISSN: 2717-414X
Homepage: https://jaree.scu.ac.ir/



Research Article

Power Resource Allocation in Downlink NOMA Systems Using Joint Sum-Rate and Bit-Error-Rate Optimization

Mohammad Hasheminejad[1], Mohsen Sheikh-Hosseini[2,*]

[1] *Department of Electrical Engineering, University of Jiroft, Jiroft, Iran*

[2] *Department of Computer and Information Technology, Institute of Science and High Technology and Environmental Sciences, Graduate University of Advanced Technology, Kerman, Iran*

* *Corresponding Author: m.sheikhhosseini@kgut.ac.ir*

Abstract: The Nonorthogonal Multiple Access (NOMA) technique is one of the key enablers of next-generation cellular communications, facilitating the sharing of the same resources among users. The effectiveness of NOMA relies heavily on implementing a robust power allocation strategy that considers diverse influential factors. To address this challenge, we propose an innovative multi-objective power allocation scheme for downlink NOMA systems using the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm. This approach simultaneously optimizes users' sum data rates and average bit error rates (BERs). The performance of the proposed method is analyzed in comparison to two benchmark approaches of Fixed Power Allocation (FSPA) and Greedy Algorithm-based Power Allocation (GAPA). The results confirm that, although our method offers comparable performance to these approaches regarding energy efficiency and sum data rate, it provides remarkable BER gain compared to these benchmarks.

Keywords: Non-Orthogonal Multiple Access (NOMA), Multi-Objective Particle Swarm Optimization (MOPSO), Power Allocation Algorithm, Sum Data Rate, Bit Error Rate (BER).

Article history
Received 06 October 2024; Revised 12 August 2025; Accepted 01 October 2025; Published 30 December 2025.
© 2025 Published by Shahid Chamran University of Ahvaz & Iranian Association of Electrical and Electronics Engineers (IAEEE)
How to cite this article
M. Hasheminejad, and M. Sheikh-Hosseini, "Power resource allocation in downlink NOMA systems using joint sum-rate and bit-error-rate optimization," *J. Appl. Res. Electr. Eng*., vol. 4, no. 1, pp. 69-75, 2025.
DOI: https://doi.org/10.22055/jaree.2025.48107.1141

Check for updates

1. INTRODUCTION

The continuous evolution of wireless technologies has led to the development of advanced cellular networks such as 5G, beyond 5G, and 6G, which promise transformative capabilities in connectivity, speed, and reliability [1-3]. However, these networks face significant challenges, including signal degradation due to channel impairments and path loss, particularly in high-frequency bands [3-5]. In the context of 5G, advanced paradigms such as cooperative communications, Device-to-Device communications, and full-duplex communication have been proposed to enhance coverage, capacity, and energy efficiency [6, 7]. Furthermore, key enablers such as massive Multiple-Input Multiple-Output (MIMO) systems, millimeter-wave communications, and ultra-dense networks (UDNs) address the limitations of conventional networks [6-8]. UDNs, by deploying a dense network of small cells, significantly improve coverage and capacity in high-demand environments. To manage this density efficiently, network slicing within virtualization frameworks allows the dynamic creation of multiple virtual networks, or "slices," each tailored to meet a specific requirement to ensure that the diverse traffic demands are met with optimized resource allocation [9].

Additionally, advanced access techniques like Non-Orthogonal Multiple Access (NOMA) have emerged as a promising technology for 5G and beyond, offering superior resource management compared to traditional orthogonal multiple access (OMA) methods [10-12]. Unlike conventional OMA schemes like TDMA, FDMA, and CDMA, NOMA allows sharing of the same resources across time, frequency, and code domains, distinguishing users by different power levels [12-14]. To ensure reliable

communication and system efficiency, the power allocation is done based on the values of the user channel gains. In particular, in the case of downlink NOMA, the available power is distributed in descending order of channel gains, enabling data recovery through Successive Interference Cancellation (SIC) at the receivers [15, 16].

Existing research on NOMA performance analysis encompasses a range of strategies aimed at enhancing various aspects, including spectral efficiency, energy efficiency, user fairness, and overall network reliability and capacity [17]. To this end, artificial intelligence tools, including various optimization techniques, have garnered significant interest in the design and optimal resource management of the NOMA scheme. The joint optimization of power allocation and channel assignment in NOMA systems is considered NP-hard due to the combinatorial nature of the problem, which involves a large search space and complex interactions between variables [15, 16, 18-22]. This difficulty arises from the need to simultaneously determine the optimum power levels for users and assign channels in a way that maximizes system performance metrics such as throughput or fairness, while also satisfying Quality of Service (QoS) constraints and system power constraints. This optimization problem is further complicated by the need to consider the decoding order for SIC and, in some cases, additional factors such as reflection coefficients in Reconfigurable Intelligent Surface (RIS)-assisted systems [8, 22]. Optimization techniques are also explored in the context of integrating NOMA with MIMO technologies, addressing resource management challenges, and implementing advanced signal processing for effective NOMA schemes [22]. Additionally, the implementation of SIC is a key factor in NOMA performance, with research indicating that optimized power allocation can significantly improve system throughput [24]. Moreover, the effects of imperfect receivers on NOMA performance have been investigated, highlighting the importance of robust SIC mechanisms [25].

The recent literature on power allocation optimization of NOMA systems has presented various strategies to enhance system performance. Reference [26] introduces a power allocation scheme for uplink NOMA systems, optimizing sum throughput under constraints using the Karush-Kuhn-Tucker conditions, showing improved throughput over OMA systems. Reference [27] extends the optimization to downlink NOMA systems, employing Lyapunov optimization to address long-term network utility maximization, overcoming the non-convex nature of the problem with a dynamic programming-based algorithm. Reference [28] proposes a dynamic power allocation strategy for uplink NOMA, which outperforms fixed power allocation, especially at low Signal-to-Noise Ratios (SNRs). In particular, reference [24] focuses on the downlink NOMA with SIC, where the proposed power allocation algorithm significantly improves system throughput compared to OMA. Reference [29] develops two power allocation strategies for downlink NOMA based on channel state information and predefined QoS, demonstrating superior performance to OMA. Reference [30] studies downlink NOMA power allocation using a genetic algorithm-based approach, achieving near-optimal performance with reduced complexity. Reference [31] analyzes NOMA in heterogeneous cloud radio access networks, proposing a joint optimization of user association, scheduling, and power allocation, showing improvements in rate, interference mitigation, and fairness. Reference [32] compares three power allocation schemes for NOMA, with full search power allocation yielding the best performance despite its complexity. Lastly, reference [33] explores a sub-optimal power allocation algorithm for 5G NOMA systems with hybrid beamforming, enhancing data flow with a low-complexity iterative technique.

Multi-objective optimization algorithms can enhance power allocation in uplink and downlink NOMA by simultaneously addressing various objectives such as maximizing throughput, energy efficiency, and fairness among users. These algorithms can provide a balance between conflicting objectives as existing works have applied various optimization techniques to address the trade-offs inherent in NOMA systems [12, 26-28].

This research aims to use multi-objective optimization tools to improve the efficiency of the power allocation algorithm in downlink NOMA systems. To be more precise, unlike most of the existing studies which often allocate power through optimizing one performance metric, we implement a Multi-Objective Particle Swarm Optimization (MOPSO) technique that simultaneously optimizes both the sum data rates of the users and the mean BER. The MOPSO algorithm is an extension of the classical Particle Swarm Optimization (PSO) method, which itself was inspired by the collective social behavior observed in fish schools and bird flocks. PSO is a population-based optimization technique in which particles iteratively adjust their positions within the search space, guided by both their own experiences and those of neighboring particles, to identify optimal solutions [34, 35]. MOPSO adapts this concept to address problems involving multiple conflicting objectives by maintaining a diverse set of solutions that approximate the Pareto front. Consequently, MOPSO combines the simplicity and efficiency of PSO with the capability to effectively tackle multi-objective optimization problems [36].

The novelties and contributions can be itemized as:

- **Novel Approach:** Unlike most proposed NOMA power allocation methods that focus solely on sum rate or BER, our approach optimizes both criteria simultaneously.
- **General Framework:** We present a flexible framework that can be adapted to various network conditions and user requirements, enhancing power allocation strategies.
- **Performance Improvement:** We conduct a comprehensive performance analysis under diverse scenarios, validating the robustness of our proposed power allocation method and highlight its advantage in terms of different key performance metrics.

The rest of this paper is organized as follows: the next section includes the signal model, problem statement, and the details of the proposed MOPSO algorithm. The third section outlines the experimental setup and discusses the results obtained. Finally, the fourth section provides a conclusion summarizing the study's key findings.

2. SUGGESTED POWER ASSIGNMENT APPROACH

2.1. System and Signal Model

Fig. 1 represents the schematic of the power-domain downlink NOMA system consisting of one base station (BS) and K users, each with one antenna. In this system, the BS divides the available power between users according to their channel gains and transmits a superimposed signal over the common channel. On the users' side, the SIC receiver is employed to remove interference and decode their data.

The model of received signal at the k^{th} user terminal will be:

$$\begin{aligned} y_k &= h_k X + n_k = h_k \sum_{k=1}^{K} \sqrt{p_k}\, x_k + n_k \\ &= h_k \left[\sum_{i=1}^{k-1} \sqrt{p_i}\, x_i + \sqrt{p_k} x_k + \sum_{i=k+1}^{K} \sqrt{p_i}\, x_i\right] + n_k \end{aligned} \quad (1)$$

in which $h_k = g_k / \sqrt{1 + d_k^{\alpha}}$ models the effective channel between the k^{th} user and the BS, where d_k stands for the distance between these two, g_k is the small-scale fading of the environment with Rayleigh distribution, and α is the path loss factor of this environment. n_k represents the noise sample at the k^{th} user terminal and follows additive white Gaussian noise (AWGN) with zero mean and variance N_0.

The parameter $X = \sum_{k=1}^{K} \sqrt{p_k}\, x_k$ represents the superposed signal of the BS terminals to be transmitted over the channel. In this formulation, p_k is the allocated power to the k^{th} user and x_k denotes the desired signal of this user which is a complex symbol of a digital modulator with the constraint of $\mathrm{E}[|x_k|^2] = 1$. As mentioned earlier, the BS assigns p_k to different users according to the values of the channel gains $|h_k|^2$. Actually, if the channel gains are sorted so that $|h_1|^2 < |h_2|^2 < \cdots < |h_K|^2$, the BS divide the available power between different users so that $p_1 > p_2 > \cdots > p_K$. This power allocation approach granitizes the reliable data recovery at the user terminals using process described in the sequel.

To recover x_k from y_k at the k^{th} user terminal, the interfering signals of all previous users, i.e., $(x_1, x_2, \ldots, x_{k-1})$, are first removed in a sequential manner using maximum likelihood (ML) detector and SIC. Then, by considering the signals of the remaining users $(x_{k+1}, x_{k+2}, \ldots, x_K)$ as interference, the ML detection is carried out to recover x_k with the below signal to interference plus noise (SINR) ratio.

$$\gamma_k = \frac{|h_k|^2 p_k}{|h_k|^2 \sum_{i=k+1}^{K} p_i + N_0} \quad (2)$$

2.2. Problem Statement and Formulation

As outlined before, this research aims to optimally allocate power resources between different users of the downlink NOMA systems by modeling this problem as a constrained multi-objective optimization problem and solving it using MOPSO. Our two objective functions are the sum of the achievable data rates and the average bit error rate of the users, where the former can be modeled using the well-known formula of information theory as

$$\begin{aligned} R &\overset{\text{def}}{=} f_1(\gamma_1, \ldots, \gamma_K) = \sum_{k=1}^{K} R_k \\ &= \sum_{k=1}^{K} \log_2(1 + \gamma_k) \\ &= \sum_{k=1}^{K} \log_2\left(1 + \frac{|h_k|^2 p_k}{N_0 + |h_k|^2 \sum_{i=k+1}^{K} p_i}\right) \end{aligned} \quad (3)$$

where R_k is the achievable data rate of k^{th} user.
In the case of the second objective function, the average BER of the system, i.e., P_e, can be formulated as

$$\begin{aligned} P_e &\overset{\text{def}}{=} f_2(\gamma_1, \ldots, \gamma_k) = \frac{1}{K} \sum_{k=1}^{K} P_{e,k} \\ &= \frac{1}{K} \sum_{k=1}^{K} f_k(\gamma_1, \ldots, \gamma_k) \end{aligned} \quad (4)$$

in which $P_{e,k}$ represents the average BER of k^{th} user. Unlike R_k, $P_{e,k}$ not only depends on its corresponding SINR γ_k, but also is a function of previous SINRs $(\gamma_1, \ldots, \gamma_{k-1})$ due to the error propagation caused by imperfect SIC at the $(x_1, \ldots, x_{k-1})$ terminals. Moreover, finding an exact expression for $f_k(\gamma_1, \ldots, \gamma_k)$ is not straightforward. Therefore, the analysis of P_e is much more complex or even impossible. As it is common, herein, we use Monte-Carlo simulation to compute this objective function. It is important to note that optimizing the first function involves maximization, while the second function needs to be minimized. Considering the relevant constraints, the proposed, multi-objective optimization problem in this research can be formulated as follows:

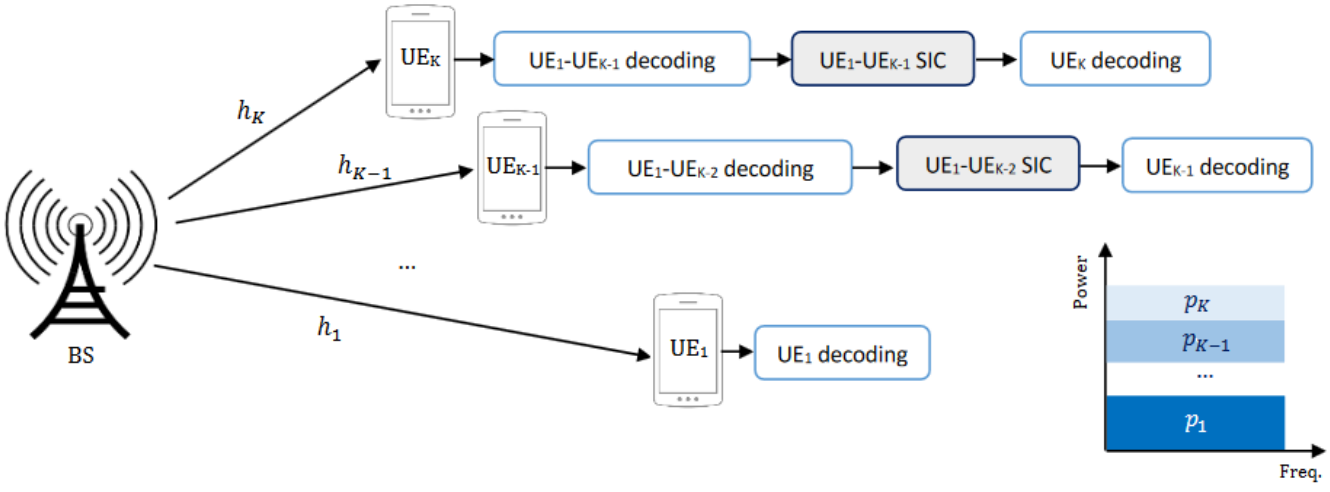


Fig. 1: A shematic of the downlink NOMA scheme with K uers [37].

$$\begin{cases} \min\limits_{p_1,\dots,p_K} & (P_e, -R), \\ subject\ to & \begin{cases} \sum_{k=1}^{K} p_k = P \\ p_1 > p_2 > \cdots > p_K \\ P_{e,k} \geq BER_{th} \end{cases} \end{cases} \quad (5)$$

where P it the total power available at the BS terminal, therefore, the constraint of $\sum_{k=1}^{K} p_k = P$ must be satisfied. In addition, BER_{th} represents a threshold which guarantees the minimum reliability required by users.

2.3. The Multi-Objective PSO Approach

The multi-objective PSO algorithm will be employed to find the optimal power allocation $\mathbf{p} = [p_1, \dots, p_K]$ that balances the two objectives. The PSO process can be described as follows:

a. Initialization:

- Each particle ($\boldsymbol{p}_i$) is a power vector that contains k elements, where each element relates to a user. The velocity vector of each particle ($\mathbf{V}_i$) represent the rate of change of a particle's power in the search space.
- Randomly initialize a swarm of particles, where each particle represents a potential solution (power allocation vector).
- Initialize each particle's position $\mathbf{p}_i$, and velocity $\mathbf{V}_i$.

b. Fitness Evaluation:

- For each particle, evaluate the fitness based on the two objectives:
- Calculate the sum rate R, and the BER for the given power allocation.
- Use a weighted approach or Pareto dominance to evaluate the performance of each particle.

c. Update Rules:

- Update the velocity and position of each particle based on its personal best position and the global best position found by the swarm.
- The updated equations are as follows:

$$\mathbf{V}_i(t+1) = \omega \mathbf{V}_i(t) + c_1 r_1 \left(\mathbf{p}_{i,\text{best}} - \mathbf{p}_i(t)\right) + c_2 r_2 \left(\mathbf{p}_{\text{global}} - \mathbf{p}_i(t)\right) \quad (6)$$

$$\mathbf{p}_i(t+1) = \mathbf{p}_i(t) + \mathbf{V}_i(t+1) \quad (7)$$

d. Termination:

- The algorithm iterates until a stopping criterion is met (e.g., a maximum number of iterations or convergence of the swarm).

2.4. Computational Complexity Analysis

The computational complexity of the proposed MOPSO algorithm can be characterized in terms of the key problem parameters. N denote the total number of users, G the group size, P the number of particles in the swarm, and I the maximum number of iterations. For a given particle, evaluating the objective functions (sum-rate and BER) involves computing the SINR, sum-rate, and BER for all groups. Under a fixed grouping strategy, this requires $O(N)$ operations per evaluation. Thus, the total complexity of MOPSO is approximately $O(P \times I \times N)$, where $P \times I$ represents the total number of candidate solutions evaluated. In following simulation settings ($P = 50$, $I = 100$), this yields 5,000 evaluations, which is tractable for NOMA scenarios with up to 12 users and results in MATLAB runtimes below two seconds on a standard desktop. Therefore, the computational cost of the proposed method is negligible compared to the substantial performance gains reported in the subsequent section.

3. Experimental Setting and Results

This section aims to evaluate the performance of the proposed Multi-Objective PSO Approach for optimizing NOMA grouping. To this end, well-known MOSPO n technique is adopted. The downlink NOMA system is implemented in MATLAB software so that a BS is located in the center of the cell with a radius of 50m, and the users are scattered randomly and uniformly inside this cell. Moreover, a Rayleigh fading channel of three taps and a path loss exponent of $\alpha = 2$ are included. The SNR per bit (E_b/N_0) changes from 0 to 40 (dB). The BPSK modulation is considered for the BS terminal and SIC receiver at the users' stations. In the simulations, two scenarios are considered for the number of users; these are $K = 6$ and $K = 12$, and a user grouping of size two is assumed in each scenario. Moreover, Fixed Power Allocation (FSPA) and Greedy Algorithm-based Power Allocation (GAPA) are utilized as benchmark methods to evaluate the performance of our proposed approach, labeled as "MOPA" in the subsequent figures, which is based on MOPSO under settings specified in Table 1. Fig. 2 and Fig. 3 represent the sum date rate results for the NOMA systems of $K = 6$ and $K = 12$, respectively. Notes, since the group size is set equal to two, it is worthing to emphasize that the number of groups in the scenarios of $N = 6$ and $N = 12$ will be three and six, respectively. The sum rate results in Fig. 2 and Fig. 3 are obtained by summing the data rates across all groups. Similarly, the spectral efficiency and BER results in the subsequent figures are derived by averaging over values of the corresponding metric over all groups. The comparison presented in these Fig. 2 and Fig. 3 reveals that, while the overall sum rate performance of the three methods is relatively similar, the FSPA method demonstrates a slight advantage over the other two. Fig. 4 and Fig. 5 illustrate the results for the energy efficiency, where the former stands for the $K = 6$ users and the latter has $K = 12$ users. As can be seen, Fig. 4 shows that the three methods perform similarly in the 6-user scenario. However, as the number of users increases to 12, the proposed method described in this study exhibits a significant performance improvement compared to the other two methods, as shown in Fig. 5.

Eventually, the BER results of both $N = 6$ and $N = 12$ scenarios are compared in Fig. 6. As seen, the advantage of the proposed method becomes evident in its substantial improvement in BER compared to the other two methods. This superiority arises from the inclusion of BER as one of the objective functions in the proposed MOPSO method, a critical consideration that is absent in the other methods. Given the pivotal role of BER in ensuring communication reliability, the proposed method's effectiveness is clearly demonstrated.

Table 1: Parameter setting of the MOPSO.

Parameter	Setting
Particle count	50
Maximum iterations	100
Weight of inertia	0.7
Factor of cognitive learning (c1)	1.5
Factor of social learning (c2)	1.5
Maximum speed	2
Elite fraction	0.7
Objectives functions	Sum-Rate and BER
Size of archive	20
Factor of exploration	0.2
Factor of exploitation	0.2

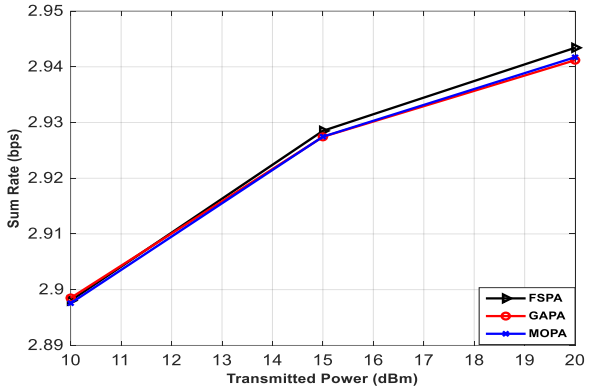


Fig. 2: Sum date rate results for the NOMA system of $K = 6$ users.

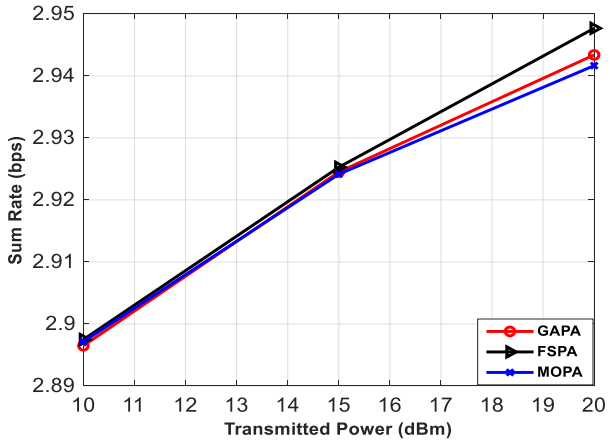


Fig. 3: Sum date rate results for the NOMA system of $K = 12$ users.

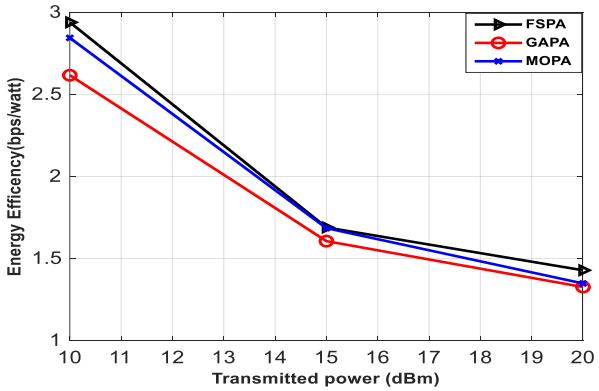


Fig. 4: Energy efficiency results for the NOMA system of $K = 6$ users.

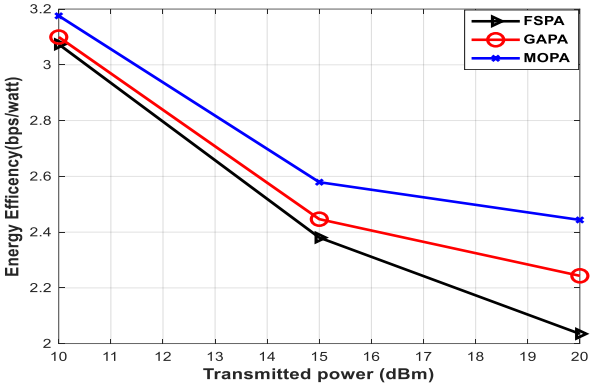


Fig. 5: Energy efficiency results for the NOMA system of $K = 6$ users.

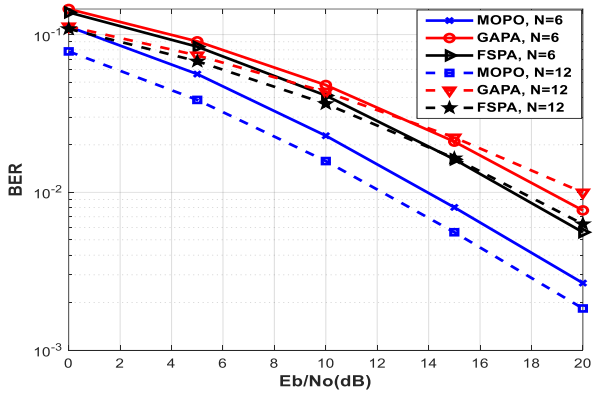


Fig. 6: BER results for the NOMA systems of $K = 6$ and $K = 12$ users.

4. Conclusion

In this paper, a novel MOPSO-based method is proposed for power allocation in downlink NOMA systems, effectively addressing the dual objectives of minimizing BER and maximizing the sum rate. The method identifies the optimal Pareto front for power allocation by categorizing users based on channel gain, enabling a balanced trade-off between these two key performance metrics. This study is particularly noteworthy as it simultaneously considers both BER and sum rate, diverging from conventional approaches that often prioritize one metric to the other. The proposed solution outperforms two benchmark methods, Fixed Power Allocation (FSPA) and Greedy Algorithm-based Power Allocation (GAPA), in terms of BER. Additionally, the comparative analysis demonstrates that the proposed method achieves performance comparable to these benchmarks in terms of spectral efficiency and sum rate.

Acknowledgment

This research was supported by University of Jiroft under the grant No 5812-02-03.

Credit Authorship Contribution Statement

Mohammad Hasheminejad: Conceptualization, Methodology, Software, Validation, Writing - review & editing. **Mohsen Sheikh-Hosseini**: Conceptualization, Methodology, Supervision, Validation, Writing - review & editing.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues; including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy has been completely observed by the authors.

REFERENCES

[1] C.-X. Wang *et al.*, "On the Road to 6G: Visions, Requirements, Key Technologies, and Testbeds," *IEEE Commun. Surv. Tutorials*, vol. 25, no. 2, pp. 905–974, 2023.

[2] M. Sheikh-Hosseini, F. Rahdari, H. Ghasemnezhad, S. Ahmadi, and M. Uysal, "A comparative performance evaluation of OFDM, GFDM, and OTFS in impulsive noise channels," *IEEE Open J. Commun. Soc.*, pp. 1–1, 2024.

[3] M. Chafii, L. Bariah, S. Muhaidat, and M. Debbah, "Twelve scientific challenges for 6G: Rethinking the foundations of communications theory," *IEEE Commun. Surv. Tutorials*, vol. 25, no. 2, pp. 868–904, 2023.

[4] T. Yenealem and R. Getachew, "Selection and tuning propagation path loss model for Hawassa city, Ethiopia at 1800 MHz frequency," *J. Appl. Res. Electr. Eng.*, vol. 2, no. 2, pp. 127–135, 2023.

[5] M. Basiri Abarghouei and R. Saadat, "Full-Duplex device-to-device relays in a novel hybrid and adaptive joint relaying network: Symbol error analysis and optimum power allocation," *J. Appl. Res. Electr. Eng.*, vol. 2, no. 2, pp. 194–205, 2024.

[6] S. Kumar, A. S. Dixit, R. R. Malekar, H. D. Raut, and L. K. Shevada, "Fifth generation antennas: a comprehensive review of design and performance enhancement techniques," *IEEE Access*, vol. 8, pp. 163568–163593, 2020.

[7] B. Sadeghi, and S. M. S. Sadough, "IRS-Assisted visible light communication for improved monitoring of patient vital signals in hospital environment," *J. Appl. Res. Electr. Eng.*, vol. 3, no. 2, pp. 240–249, 2025.

[8] F. Rahdari, M. Sheikh-Hosseini, and M. Jamshidi, "Edge user performance improvement by intelligent reflecting surface-assisted NOMA system," *J. Electr. Comput. Eng. Innov.*, pp. 275–282, 2024.

[9] P. A. D. S. N. Wijesekara, "Network virtualization utilizing blockchain: A review," *J. Appl. Res. Electr. Eng.*, vol. 3, no. 2, pp. 136–158, 2024.

[10] T. O'Shea and J. Hoydis, "An introduction to deep learning for the physical layer," *IEEE Trans. Cogn. Commun. Netw.*, vol. 3, no. 4, pp. 563–575, Dec. 2017.

[11] R. Shafin, L. Liu, V. Chandrasekhar, H. Chen, J. Reed, and J. C. Zhang, "Artificial intelligence-enabled cellular networks: A critical path to beyond-5G and 6G," *IEEE Wirel. Commun.*, vol. 27, no. 2, pp. 212–217, Apr. 2020.

[12] C. Zhang, P. Patras, and H. Haddadi, "Deep learning in mobile and wireless networking: A survey," *IEEE Commun. Surv. Tutorials*, vol. 21, no. 3, pp. 2224–2287, 2019.

[13] M. Eisen, C. Zhang, L. F. O. Chamon, D. D. Lee, and A. Ribeiro, "Learning optimal resource allocations in wireless systems," *IEEE Trans. Signal Process.*, vol. 67, no. 10, pp. 2775–2790, May 2019.

[14] J. Kaur, M. A. Khan, M. Iftikhar, M. Imran, and Q. Emad Ul Haq, "Machine learning techniques for 5G and beyond," *IEEE Access*, vol. 9, pp. 23472–23488, 2021.

[15] L. Salaun, C. S. Chen, and M. Coupechoux, "Optimal Joint subcarrier and power allocation in NOMA is strongly NP-Hard," in *2018 IEEE International Conference on Communications (ICC)*, May 2018, pp. 1–7.

[16] G. Liang, Q. Zhu, J. Xin, Y. Feng, and T. Zhang, "Joint user-channel assignment and power allocation for non-orthogonal multiple access relaying networks," *IEEE Access*, vol. 7, pp. 30361–30372, 2019.

[17] V. Vishalakshi and G. Shivsharanappa Biradar, "A taxonomy on power optimization techniques for fifth-generation heterogenous non-orthogonal multiple access networks," *Int. J. Electr. Comput. Eng.*, vol. 14, no. 2, pp. 1616–1624, Apr. 2024.

[18] J. Cui, Z. Ding, and P. Fan, "Beamforming design for MISO non-orthogonal multiple access systems," *IET Commun.*, vol. 11, no. 5, pp. 720–725, Mar. 2017.

[19] L. Lei, D. Yuan, C. K. Ho, and S. Sun, "Joint optimization of power and channel allocation with non-orthogonal multiple access for 5G cellular systems," in *2015 IEEE Global Communications Conference (GLOBECOM)*, Dec. 2015, pp. 1–6.

[20] J. Zhu, J. Wang, Y. Huang, S. He, and X. You, "Multichannel resource allocation for downlink non-orthogonal multiple access systems," in *GLOBECOM 2017 - 2017 IEEE Global Communications Conference*, Dec. 2017, pp. 1–6.

[21] J. Zhu, J. Wang, Y. Huang, S. He, X. You, and L. Yang, "On optimal power allocation for downlink non-orthogonal multiple access systems," *IEEE J. Sel. Areas Commun.*, pp. 1–1, 2017.

[22] J. Zuo, Y. Liu, Z. Qin, and N. Al-Dhahir, "Resource Allocation in Intelligent Reflecting Surface Assisted NOMA Systems," *IEEE Trans. Commun.*, vol. 68, no. 11, pp. 7170–7183, Nov. 2020.

[23] Y. Liu, H. Xing, C. Pan, A. Nallanathan, M. Elkashlan, and L. Hanzo, "Multiple-Antenna-Assisted non-orthogonal multiple access," *IEEE Wirel. Commun.*, vol. 25, no. 2, pp. 17–23, Apr. 2018.

[24] T. Manglayev, R. C. Kizilirmak, and Y. H. Kho, "Optimum power allocation for non-orthogonal multiple access (NOMA)," in *2016 IEEE 10th International Conference on Application of Information and Communication Technologies (AICT)*, Oct. 2016, pp. 1–4.

[25] U. Sharma, P. Singh, and M. Awasthi, "Non-Orthogonal Multiple Access (NOMA) for 5G radio technology," in *Proceedings of Third Doctoral Symposium on Computational Intelligence*, 2023, pp. 523–532.

[26] H. Zuo and X. Tao, "Power allocation optimization for uplink non-orthogonal multiple access systems," in *2017 9th International Conference on Wireless Communications and Signal Processing (WCSP)*, Oct. 2017, pp. 1–5.

[27] W. Bao, H. Chen, Y. Li, and B. Vucetic, "Joint rate control and power allocation for non-orthogonal multiple access systems," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 12, pp. 2798–2811, Dec. 2017.

[28] X. Wang, T. Xu, T. Zhou, and H. Hu, "Dynamic power allocation strategy for uplink non-orthogonal multiple access systems," *Comput. Commun.*, vol. 184, pp. 36–41, Feb. 2022.

[29] M. M. El-Sayed, A. S. Ibrahim, and M. M. Khairy, "Power allocation strategies for non-orthogonal multiple access," in *2016 International Conference on Selected Topics in Mobile & Wireless Networking (MoWNeT)*, Apr. 2016, pp. 1–6.

[30] W. F. Alghasmari and L. Nassef, "Optimal power allocation in downlink Non-Orthogonal Multiple Access (NOMA)," *Int. J. Adv. Comput. Sci. Appl.*, vol. 12, no. 2, 2021.

[31] R. Rai, H. Zhu, and J. Wang, "Coordinated scheduling and power control for Non-Orthogonal Multiple Access (NOMA) enabled H-CRAN," in *2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring)*, May 2020, pp. 1–5.

[32] W. F. Alghasmari and L. Nassef, "Power allocation evaluation for downlink Non-Orthogonal Multiple Access (NOMA)," *Int. J. Adv. Comput. Sci. Appl.*, vol. 11, no. 4, 2020.

[33] N. Alzubaidi and I. S. Hubri, "Non-Orthogonal Multiple Access (NOMA) dynamic power allocation in 5G networks," *Wasit J. Eng. Sci.*, vol. 10, no. 2, pp. 111–118, Jul. 2022.

[34] Ni. K. Prah II, E. Twumasi, and E. A. Frimpong, "Combined economic emission dispatch in a grid-connected microgrid using an improved mayfly algorithm," *J. Appl. Res. Electr. Eng.*, vol. 2, no. 2, pp. 112–119, 2023.

[35] E. Farahmand and A. Mahani, "A novel energy-efficient weighted multi-level clustering protocol," *J. Appl. Res. Electr. Eng.*, vol. 1, no. 1, pp. 69–78, 2022.

[36] Coello, Carlos A. Coello, Gregorio Toscano Pulido, and Maximino Salazar Lechuga, "Handling multiple objectives with particle swarm optimization," *IEEE Trans. Evol. Comput.*, vol. 8, no. 3, 256-279, 2004.

[37] F. Rahdari and M. Sheikh-Hosseini, "Nonlinear symbolic regression for bit error rate prediction of NOMA systems in 5G cellular communications," *Eng. Appl. Artif. Intell.*, vol. 127, Art. no. 107344, Jan. 2024.

BIOGRAPHY



Mohammad Hasheminejad is an accomplished Assistant Professor at the University of Jiroft in the Kerman province, Iran, specializing in Telecommunication Engineering. Having earned a PhD in 2016, from university of Birjand, in the field of Telecommunication Engineering, he has since been an active researcher with a keen interest in data science, artificial intelligence, and robotics. Proficient in MATLAB and Python programming, Dr. Mohammad Hasheminejad has made significant contributions to the field and has been recognized with three awards as one of the best researchers in 2023 at the University of Jiroft. With a strong publication record and a dedication to advancing the frontiers of technology.



Mohsen Sheikh-Hosseini received his B.S. degree in Electrical Engineering from Shahid Bahonar University of Kerman, Iran, in 2007. He completed his M.Sc. and Ph.D. in Telecommunications Engineering from Ferdowsi University of Mashhad, Iran, in 2009 and 2014, respectively. He is currently a faculty member at the Department of Computer and Information Technology, Graduate University of Advanced Technology, Kerman, Iran. His research interests include communications theory, focusing on designing emerging physical layer waveforms, performance analysis of impulsive noise channels, and the application of AI in telecommunications. He is also interested in both wireless and wireline telecommunications technologies, particularly cellular communications, power line communications (PLC), and smart grid communications.

Copyrights
© 2025 Licensee Shahid Chamran University of Ahvaz, Ahvaz, Iran. This article is an open-access article distributed under the terms and conditions of the Creative Commons Attribution –Non-Commercial 4.0 International (CC BY-NC 4.0) License (http://creativecommons.org/licenses/by-nc/4.0/).