SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V13I9P112
Volume 13 Issue 9, 195-207, September 2026

Original Article

Performance Improvement in QoS Metrics: Implementing Dynamic Power Allocation using Surrogate Optimization in Clustered NOMA for 5G and Beyond 5G Networks

Lekshmi Nair M[1*,2,3], Neelakantan PC[4]

[1]*Research Scholar, APJ Abdul Kalam Technological University, Trivandrum, Kerala, 695016, India*
[2]*Assistant Professor, Department of Electronics and Communication, SCMS School of Engineering and Technology, Ernakulam, Kerala, 683576, India*
[3] *Research Scholar, Adi Shankara Institute of Engineering & Technology, Kalady, Kerala, 683574, India*
[4] *Professor, Muthoot Institute of Technology and Science, Ernakulam, Kerala, 682308, India*

[*]*Corresponding Author : lekshmi8887@gmail.com*

Received: 05 June 2026 Revised: 12 August 2026 Accepted: 19 August 2026 Published: 29 September 2026

Abstract - *This paper proposes a regression-based surrogate optimization framework for dynamic power allocation in downlink clustered Non-Orthogonal Multiple Access systems (NOMA). The inherent non-convexity of the power allocation problem is addressed, and user power coefficients are adaptively optimized using a Karush-Kuhn-Tucker-based closed-form expression. Simulation results demonstrate that dynamic power allocation using the proposed surrogate method significantly reduces outage probability as low as 10^{-4} at higher transmit power levels. The cluster average data rate is enhanced by approximately 8% over static NOMA and achieves nearly eight times higher performance compared to Orthogonal Multiple Access (OMA). At the individual user level, dynamic power allocation provides a substantial user rate improvement than static power allocation, indicating enhanced fairness and efficient utilization of resources. The simulation results confirm that the proposed surrogate optimization framework effectively transforms the non-convex power allocation problem into a tractable form. This enables adaptive power control that improves SINR, mitigates interference, and maximizes spectral efficiency. Also, the proposed dynamic power allocation strategy offers a robust and scalable solution for enhancing both reliability and throughput, making it suitable for future generations of wireless networks.*

Keywords - *Cluster, Dynamic power allocation, Karush-Kuhn-Tucker condition, Outage probability. Power Domain NOMA, Surrogate optimization.*

1. Introduction

The exponential increase in wireless data demand, driven by the widespread adoption of smart devices and the rise of data-intensive applications, has necessitated the development of advanced multiple access schemes for next-generation wireless communication systems [1]. Non-Orthogonal Multiple Access (NOMA) has gained significant attention as a key enabler for 5G and beyond, owing to its ability to support multiple users concurrently over the same time-frequency resources through power-domain multiplexing [2]. With the increasing demand for higher data rates and rapidly growing network traffic, NOMA has gained recognition as one of the finest enabling technologies for Fifth-Generation (5G) and beyond 5G networks [3]. In NOMA, multiple users share the same resources simultaneously, with differentiation achieved through distinct power levels [4]. The core principle involves non orthogonal superposition of user signals in the power domain or in the code domain, enabling simultaneous transmission and efficient spectrum utilization [5]. The advantage of having increased spectral efficiency is often compensated by the increased interference between the users [6].

In multiuser NOMA, each User Equipment (UE) is served by beams, based on the availability of transmitting and receiving antennas at the Base Station (BS) and the UEs in the cell, respectively. Each UE receiver is assigned a dedicated beamforming vector, specifically designed to be orthogonal to the channel gains of other receivers [7]. In a cluster-based scenario, users are organized into clusters for efficient resource allocation. Interference management, with NOMA applied exclusively within each cluster [8]. The user pairing process determines the selection and grouping of users within a specific cluster. Clustering plays an important role in optimizing system performance by balancing trade-offs between spectral efficiency, user fairness, and computational complexity [9]. NOMA enhances spectrum utilization by strategically allocating resources to users within a cluster.

Power Allocation (PA) is a fundamental resource management mechanism in NOMA that determines how transmission power is distributed among users [10]. Power allocation approaches are broadly categorized as static or dynamic, depending on their level of adaptability to channel conditions. Static Power Allocation (static PA) allocates fixed power coefficients to users, which are determined by predefined criteria such as channel ranking or fairness considerations [11]. This approach is easier to implement, but it lacks adaptability to real-time channel fluctuations, which often degrades system performance. In contrast, Dynamic Power Allocation (dynamic PA) adjusts power levels in real time depending on Channel State Information (CSI), Quality-of-Service (QoS) demands, and prevailing interference conditions. It provides greater adaptability and enhanced performance [12].

In practical clustered NOMA deployments, the power allocation problem becomes challenging as the number of clusters and users increases. This happens because each user's achievable rate depends not only on the power split within its own cluster but also on the aggregate transmit power of neighbouring clusters. So, the sum-rate maximisation problem becomes non-convex, and existing solution strategies address it through iterative convex reformulation. This requires repeated re-linearisation and can be slow to converge. A closed-form, low-complexity framework that handles both interference terms accurately is therefore needed before dynamic power allocation can be deployed at scale.

To facilitate NOMA transitions from theoretical frameworks to practical implementation, a comprehensive understanding of static versus dynamic power allocation strategies is essential. The literature review systematically analyses both approaches, focusing on their design principles, performance implications, and the inherent trade-offs associated with their deployment.

2. Literature Review

Power allocation schemes play significant roles in NOMA systems, offering different approaches to optimize performance and resource utilization [13]. Static power allocation uses fixed transmit power coefficients based on long-term channel statistics such as average channel gain, distance, or path loss without utilizing instantaneous CSI, resulting in low signalling overhead and computational complexity [14]. Users are ordered based on long-term channel statistics, such as average channel gains[15]. Power allocation follows the SIC decoding hierarchy, which offers low computational complexity. Joint optimization of user pairing and power allocation is discussed in [16] under perfect and imperfect SIC to achieve higher spectral efficiency and sum rate, coupled with reduced outage.

A classification of static power NOMA named Fair-NOMA ensures that each user attains at least its OMA capacity by analytically defining a feasible power-allocation region [17] that increases both individual and sum rates. Better ergodic sum-rate gains at high SNR and enhanced weak-user outage performance are achieved without requiring additional transmit power. Fair-NOMA has been extended to K-user systems in [18], where it analytically proposes an optimal downlink multi-user NOMA power-allocation strategy that maximizes sum rate, along with superior spectral efficiency and fairness over OMA, fixed-NOMA, and benchmark methods.

Gain Ratio Power Allocation (GRPA) is another approach of static NOMA that enhances fairness and sum rate by allocating power using the ratio of each user’s channel gain to that of the strongest user. It introduces limited channel awareness while preserving the low complexity of static schemes. In [19, 20], GRPA-based location-aware power allocation schemes for VLC NOMA improve data rate, spectral efficiency, and inter-cell interference management over OMA. However, their static channel ratio dependence and iterative location-sensitive optimisation limit adaptability and scalability in dynamic environments. In [21, 22], gain difference-based power allocation schemes for VLC NOMA allocate transmit power to users based on channel conditions and optical parameters to enhance fairness, throughput, spectral efficiency, and BER. Normalised Gain Difference Power Allocation (NGDPA) in [23] allocates power using normalized channel gain differences in indoor MIMO PD-NOMA VLC systems, achieving enhanced sum-rate gain over GRPA with low complexity.

An optimal power allocation problem is presented as a sum-rate maximization problem in [24], subject to constraints on the maximum number of users per subcarrier and the individual user power constraints. The authors demonstrated that power allocation has a substantial effect on the achievable performance metrics of the proposed NOMA scheme.

The outage probability and diversity order obtained by the cooperative NOMA scheme under static power allocation strategies are discussed in [25]. In [26], power allocation allows the cell-edge user to be supported using the Alamouti code transmitted from the two coordinated base stations, without degrading the rates to the near users. The results presented in [27] demonstrate that MIMO-NOMA, employing a straightforward fixed power allocation scheme, can outperform conventional MIMO-OMA in terms of outage probability, even for users subjected to strong co-channel interference. The authors in [28] discussed how power allocation coefficients impact the performance of the 2 schemes - fixed power allocation NOMA and cognitive-inspired NOMA. The results highlighted the performance superiority of cognitive-inspired NOMA over traditional NOMA schemes.

The authors in [29] discussed a three-step resource allocation strategy used for sum rate maximization of users. The users with distinct user gains are paired in [30], and an enhanced sum rate is obtained using a deep learning power allocation method. The significance of power allocation in minimizing outage probability using a Genetic Algorithm is discussed in [31].

An analysis of existing static power allocation strategies in NOMA systems reveals several key limitations. The drawbacks mainly include rigid QoS adaptation and suboptimal weak performance. Static power allocation often fails to adapt to users' specific QoS demands. This analysis suggests dynamic power allocation could overcome these constraints while retaining NOMA's spectral efficiency advantages.

Dynamic power allocation in NOMA adapts to varying channel conditions and user demands, offering enhanced flexibility and performance. Authors in [32] introduced an innovative Dynamic Power Allocation Scheme For Hybrid NOMA (DH-NOMA), which achieves superior outage performance compared to conventional orthogonal multiple access. It achieves a better effective balance between user rates than Fixed Power Allocation (F-NOMA) and Cognitive Radio-Inspired NOMA (CR-NOMA). However, the paper lacks detailed guidance on the optimal selection of the dynamic factor β, which may be critical for ensuring the scheme's effectiveness across various scenarios**.** Similarly, another dynamic scheme proposed [33] for both downlink and uplink NOMA scenarios provides greater flexibility in achieving various trade-offs between user fairness and overall system throughput.

Power allocation in dynamic OFDM NOMA is convexified in [34], and subcarriers are iteratively updated using a deletion algorithm to outperform OFDMA and static NOMA under perfect CSI. Authors in [35] derived closed-form KKT-based power coefficients for two-path AF relay NOMA, which increases spectral efficiency. Massive IoT and dense network extensions in [36, 37] adopted convex optimization and SQP-based power control to mitigate imperfect SIC and scalability issues, offering notable capacity and spectral-efficiency gains. Multi-carrier clustered NOMA in [38] adopted water-filling-based convex formulations to improve sum rate, fairness and outage, but the gain is diminished with an increase in cluster size. A cooperative NOMA with Simultaneous Wireless Information and Power Transfer (SWIPT) relay network with time-division resource allocation is examined in [39], which applies a generalized Dinkelbach algorithm to maximize energy efficiency in both direct and cooperative modes. It achieves fast convergence and notable energy efficiency gains with low complexity. A dynamic joint user scheduling and power allocation scheme for downlink NOMA under imperfect CSI is discussed in [40]. A probabilistic non-convex formulation is converted into a deterministic iterative solution here. Energy efficiency and outage performance are increased, but scalability challenges occur due to CSI sensitivity.

Max-Min Fairness (MMF) optimisation maximises the minimum achievable user rate, thereby supporting weak users, ensuring equitable resource allocation. A notable improvement in edge user performance and fairness is obtained using MMF optimization along with KKT conditions and bisection methods [41] when compared with conventional MIMO-NOMA and sum rate-oriented designs. Dynamic programming-based user selection and gradient-based power control are studied in multicarrier NOMA [42], achieving near-optimal spectral efficiency with reduced complexity. Cross-cluster and joint resource allocation strategies in [43] effectively balance user fairness and spectral efficiency in NOMA by guaranteeing weak-user QoS while sustaining competitive system throughput.

Genetic Algorithms (GA) explore large solution spaces and adapt power allocation based on parameters like channel conditions, user distance, and modulation schemes. GA based frameworks in [44] jointly optimize user grouping and power allocation for downlink NOMA-OFDM to maximize geometric-mean throughput, achieving near-exhaustive-search performance and improved fairness. Complexity is reduced here, but under assumptions of perfect SIC and fixed system parameters. A three-user PD NOMA implementing GA based fair power allocation strategy was introduced in [45]. Transmit power is adjusted dynamically based on channel and modulation conditions. Improved BER and fairness improvement were obtained at the cost of increased iterative complexity.

In [46], a Simulated-Annealing (SA) based scheme that jointly optimizes user pairing and power allocation scheme for downlink NOMA was presented. Throughput and gain were maximised with reduced complexity. However, the scenario is limited to two-user pairing and is sensitive to parameter tuning. Broadening SA to scheduling problems, [47] proposes a serial collaborative SA framework for uplink span, significantly outperforming OMA and random NOMA under simplified assumptions such as fixed power and two-user clusters.

In [48], a Modified Artificial Bee Colony Algorithm (MABC) based downlink NOMA power allocation framework incorporates optimization of power coefficients under total power and minimum rate constraints. The proposed scheme achieves faster convergence and higher throughput than OMA, offering limited scalability in dynamic scenarios. Table 1 shows some related works that implemented dynamic power allocation methods in NOMA schemes. Based on the comprehensive literature review, a concise comparison between static and dynamic power allocation schemes in NOMA is identified.

Table 2 gives a brief description of the comparison of QoS parameters of static and dynamic power allocation schemes. Despite the substantial body of work summarised above, three gaps remain open in the literature on power allocation for clustered NOMA. First, static allocation schemes achieve low complexity but cannot adapt to instantaneous channel state information, and therefore cannot guarantee QoS under fading. Second, dynamic schemes based on convex reformulation, genetic algorithms, simulated annealing, or reinforcement learning adapt to CSI but introduce iterative or learning-based computational overhead that scales poorly with the number of clusters. Several of them (e.g., [32, 46, 47]) further rely on simplifying assumptions, such as two-user pairing or perfect SIC, that limit their applicability to general multi-cluster networks.

Third, and most critically, none of the existing dynamic schemes jointly account for intra-cluster and inter-cluster interference within a single closed-form update rule. Inter-cluster interference is typically either ignored or handled through a separate, additional optimisation layer.

This work addresses all three gaps by formulating a regression-based surrogate model that locally approximates the non-convex, interference-coupled rate function with a concave lower-bound surrogate, and by deriving a Karush-Kuhn-Tucker-based closed-form power update from this surrogate.

The resulting scheme adapts to instantaneous CSI like other dynamic methods, but avoids the iterative re-solving and training overhead of convex-reformulation and learning-based approaches, while explicitly capturing both interference terms in a single expression.

The rest of the paper is organized as follows. Section 3 explains motivations and contributions. Section 4 presents the proposed system model. Results and discussions are described in Section 5. Section 6 highlights the conclusion of the paper.

Table 1. Dynamic power allocation schemes in NOMA

Scenario	Strategy adopted	Merits	Demerits	Ref.
Downlink multi-carrier NOMA	Weighted sum utility	Improved performance due to user diversity gain	Complex subcarrier power allocation scheme	[49]
Downlink single-cell NOMA	Actor-critic reinforcement learning	Increased Energy efficiency	Real-time application introduces complexity	[50]
Hybrid OMA-NOMA in uplink cognitive radio network	Deep actor-critic reinforcement learning	Network performance is improved	Complexity increases due to introduction of time slots to users	[51]
Downlink multicell MIMO NOMA	Joint user pairing and dynamic power allocation	Inter-user interference minimised and energy efficiency maximised	CSI introduces constraints in practical implementation	[52]
Downlink multi-channel NOMA	Dynamic power and channel allocation scheme	Increased data rate, especially for cell-edge users	Computational complexity for inter-channel power allocation in practical applications	[53]
Single cell downlink NOMA	Dynamic power allocation with user mobility	Better sum rate	Perfect CSI assumed, increasing practical constraints	[54]
Single cell downlink NOMA	Packet-level user pairing and power allocation scheme	Higher throughput for users	Limited feedback CSI	[55]
Downlink MIMO NOMA network	Beamformed MIMO-NOMA (BMN) algorithm	Increased spectral efficiency and energy efficiency	Energy efficiency declines with increase in number of users	[56]
Downlink SISO NOMA	Simulated Annealing (SA) optimisation	Better resource allocation and increased energy efficiency	Does not sufficiently represent the dynamic nature of mobile networks	[57]

Table 2. Comparison of static and dynamic power allocation schemes

QoS Parameter	Static allocation	Dynamic power allocation
BER performance	Less BER performance	Improved BER performance, especially at low relative power ratios
Outage Probability	Higher outage probability	Lower outage probability, offering better performance
Flexibility	Limited flexibility in meeting various QoS requirements	More flexible in realizing different trade-offs between user fairness and system throughput
Performance Gain	Limited performance gain over OMA	Better performance than static power allocation
User Fairness	May lead to imbalanced user rates	Achieves improved balance between individual user rates
Adaptability	Cannot adapt to changing channel conditions	Can adapt to dynamic channel conditions and QoS requirements
Complexity	Lower implementation complexity	Higher complexity due to dynamic adjustments
Power Efficiency	Less efficient power utilization	More efficient power utilization can minimize total transmit power
Robustness	Less robust to imperfect SIC and CSI	Can be optimized for robustness against imperfect SIC and CSI

3. Motivations and Contributions

The novelty of the proposed work lies in three aspects that jointly distinguish it from the dynamic power allocation schemes summarised in Table 1. First, unlike reinforcement-learning-based schemes [50, 51] that require extensive offline training and online exploration, and unlike metaheuristic schemes such as genetic algorithms [44, 45] and simulated annealing [46, 47] that require multiple population evaluations per channel realisation, the proposed method produces a power update through a single closed-form KKT expression per iteration, eliminating training overhead and reducing per-slot computation.

Second, unlike convex-reformulation schemes [34, 38] that typically model only intra-cluster interference or treat inter-cluster interference as a fixed offset, the surrogate function derived here explicitly incorporates both intra-cluster and inter-cluster interference terms into a single Taylor-linearised concave lower bound, so that the resulting power allocation accounts for the aggregate impact of neighbouring clusters rather than approximating it.

Third, the surrogate reformulation converts a non-convex rate-coupled problem into a sequence of convex sub-problems that are solved in closed form, avoiding the iterative numerical solvers (e.g., interior-point or SQP-based solvers used in [36, 37]) that dominate the runtime of prior convex approaches. Together, these three elements yield a scheme that combines the adaptability of dynamic power allocation with a complexity profile closer to that of static schemes, which the literature review indicates has not previously been demonstrated for clustered multi-user NOMA.

The contribution of this work is as follows:

- Introduction of a regression-based Surrogate Optimization framework in a downlink cluster NOMA scenario that dynamically adjusts power coefficients, enabling real-time and low-complexity adaptation.
- The inherent non-convexity of the power allocation problem is addressed, and adaptive optimization of user power coefficients is done using a Karush-Kuhn-Tucker-based closed-form expression.
- Extensive simulation results demonstrating the superiority of dynamic power allocation in reducing outage probability and improving individual data rate and average cluster data rate when compared with static power allocation schemes and OMA.

Table 3 compares the current work with existing research findings.

Table 3. Comparison of current work with existing research findings

Aspect	Static PA (Fair-NOMA, GRPA)	GA / SA-based Dynamic PA [44-47]	RL-based Dynamic PA [50, 51]	Convex-reformulation Dynamic PA [34, 38]	Proposed method-Surrogate + KKT
CSI adaptivity	No	Yes	Yes	Yes	Yes
Interference handled	Not modelled	Intra-cluster only	Intra-cluster only	Intra-cluster; inter-cluster approximated/ignored	Intra- and inter-cluster jointly, in closed form
Solution form	Closed-form	Population-	Trained policy	Iterative convex solver	Closed-form

	(fixed)	based search (iterative)	(needs offline/online learning)	per slot	KKT update per iteration
Computational overhead	Very low	High (multiple candidate evaluations)	High (training) + moderate (inference)	Moderate–high	Low (single closed-form update per iteration)
Scalability with cluster count	Good, but performance poor	Degrades with search space size	Degrades with state-action space size	Degrades with solver iterations	Scales linearly with clusters (closed-form)

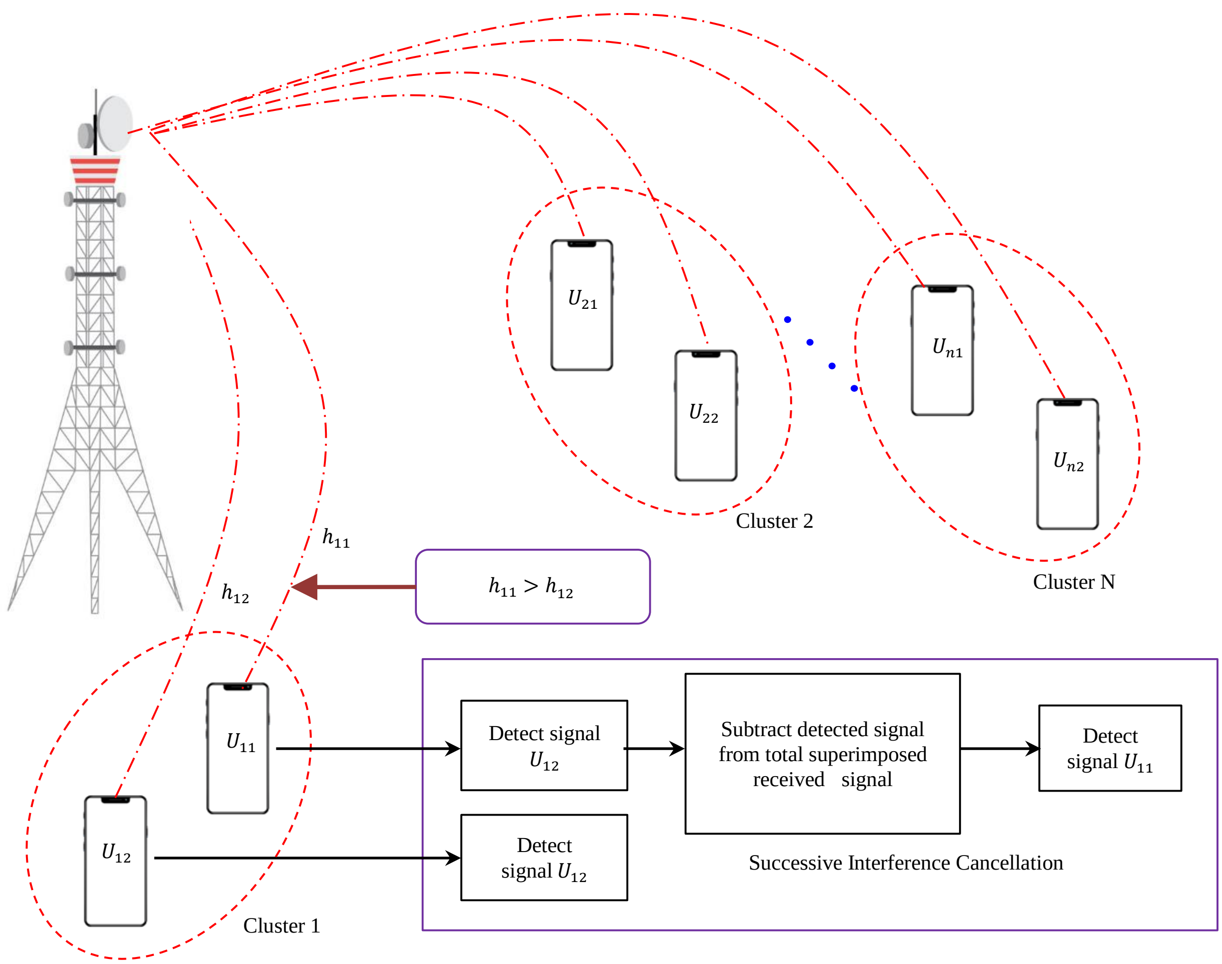

Fig. 1 Network architecture of Cluster NOMA

4. System Model

Consider Power Domain Multi-Cluster NOMA in a downlink scenario, as in Figure 1. Two users are assumed inside each cluster, with user 1(having a good channel condition and user 2 (having a poor channel condition. Superposition coding is implemented at the transmitter side, and successive interference cancellation is implemented at the receiver side.

Since it is a multi-cluster NOMA scenario, intra-cluster interference and inter-cluster interference simultaneously affect the system performance. Surrogate optimization is employed to solve a non-complex power allocation problem arising due to inter-cluster interference. The interference-dependent term is approximated using Taylor expansion at a given point, which results in a concave lower-bound surrogate function that locally represents the achievable-rate expression. The optimisation problem is solved iteratively, where power allocation is updated using a Karush-Kuhn-Tucker (KKT)-based closed-form expression. This process is repeated until convergence, which provides near-optimal performance under practical interference conditions.

Let s_1 and s_2 be message signals of users 1 and 2, respectively, in cluster 1. The gain of the channel is denoted as h_i with $h_1 > h_2 > \cdots h_n$. Total transmit power in the cluster is denoted as P. Noise power is denoted as σ^2. Power allocation coefficients of user 1 and 2 are denoted as α_1 and α_2 with $\alpha_1 + \alpha_2 = 1(\alpha_1 < \alpha_2)$. Power allotted to each user is denoted as $p_1 = \alpha_1 P$, $p_2 = \alpha_2 P$,……. $p_i = \alpha_i P$

For user i, the SINR is:

$$SINR_i = \frac{p_i\,|h_i|^2}{\sum_{j=1}^{i-1} p_j\,|h_i|^2 + \sum_{c\in K}\sum_{k\in \mathrm{U}_c} p_{k,c}\,|h_{k,c}|^2 + \sigma^2} \qquad (1)$$

Where: $p_j\,|h_i|^2$ is the intra-cluster interference

$\sum_{c\in K}\sum_{k\in \mathrm{U}_c} |\,p_{k,c}\,h_{k,c}|^2$ is the inter-cluster interference, where:

- K = set of clusters
- $h_{k,c}$ = interfering channel
- $p_{k,c}$ = interfering power

Sum rate of users is given as:

$$R_{sum} = \sum_{i=1}^{K} \log_2\left(1 + \frac{p_i\,|h_i|^2}{\sum_{j=1}^{i-1} p_j\,|h_i|^2 + \sum_{c\in K}\sum_{k\in \mathrm{U}_c} p_{k,c}\,h_{k,c}|^2 + \sigma^2}\right) \qquad (2)$$

Let interference plus noise term is defined as:

$$I_i = \sum_{j=1}^{i-1} p_j\,|h_i|^2 + \sum_{c\in K}\sum_{k\in \mathrm{U}_c} p_{k,c}\,|h_{k,c}|^2 + \sigma^2 \qquad (3)$$

So, the SINR becomes:

$$SINR_i = \frac{p_i\,|h_i|^2}{I_i} \qquad (4)$$

Rate expression is given as:

$$R_i = \log_2\left(1 + \frac{p_i\,|h_i|^2}{I_i}\right) \qquad (5)$$

Now rewrite using a log identity:

$$R_i = \log_2(I_i + p_i\,|h_i|^2) - log_2(I_i) \qquad (6)$$

Since $log_2(I_i)$ is concave, it can be approximated using a first-order Taylor expansion.

At iteration k, expand around. $I_i^{(k)}$

$$\log(I_i) \approx \log(I_i^{(k)}) + \frac{1}{I_i^{(k)}}(I_i - I_i^{(k)}) \qquad (7)$$

Converting to base 2,

$$\log_2(I_i) \leq log_2(I_i^{(k)}) + \frac{1}{\ln 2}\left(\frac{I_i - I_i^{(k)}}{I_i^{(k)}}\right) \qquad (8)$$

Now apply a negative sign,

$$-\log_2(I_i) \geq -\,log_2(I_i^{(k)}) - \frac{1}{\ln 2}\left(\frac{I_i - I_i^{(k)}}{I_i^{(k)}}\right) \qquad (9)$$

This inequality provides a lower bound for the negative logarithmic interference term.

Constructing Surrogate Rate Function:

$$\widetilde{R_i^{(k)}} = log_2(I_i + p_i\,|h_i|^2) - \left[log_2(I_i^{(k)}) + \frac{1}{ln\,2}\left(\frac{I_i - I_i^{(k)}}{I_i^{(k)}}\right)\right] \qquad (10)$$

Surrogate Optimization Problem is defined as:

At iteration k:

$$\max_P \sum_{i=1}^{K} \widetilde{R_i^{(k)}} \qquad (11)$$

Subject to

$$\sum_{i=1}^{K} p_i < P$$

$$p_i \geq 0$$

$$\widetilde{R_i^{(k)}} \geq R_i^{min}$$

Outage threshold can be set as:

$$\gamma_i^{th} = 2^{R_i^{min}} - 1 \qquad (12)$$

Then the outage condition is defined as

$$P_i^{out} = \Pr\left(\frac{p_i\,|h_i|^2}{\sum_{j=1}^{i-1} p_j\,|h_i|^2 + \sum_{c\in K}\sum_{k\in \mathrm{U}_c} p_{k,c}\,h_{k,c}|^2 + \sigma^2} \leq \gamma_i^{th}\right) \qquad (13)$$

The algorithm and flow chart for finding the required user power using the surrogate optimization method are described below. The resulting convex optimization problem is solved, whose objective is the concave surrogate rate function, to obtain the optimal power allocation by applying the KKT conditions. The solution explicitly captures the impact of channel gain, intra-cluster interference, inter-cluster interference, and the surrogate approximation parameters. Proper selection of initial parameters and convergence tolerance plays a crucial role in providing a fair power allocation to all users in the system.

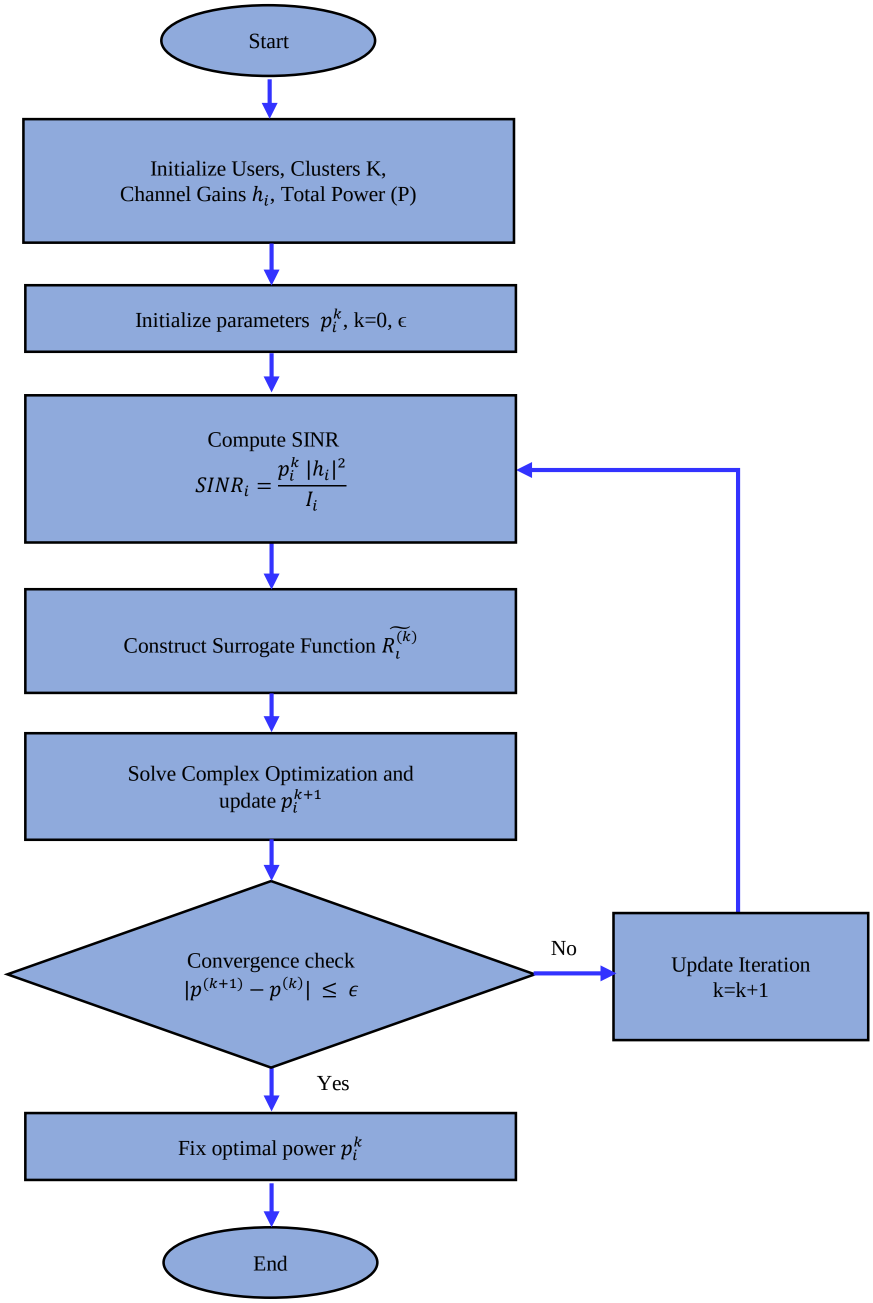

Fig. 2 Flow chart for finding the power allocation factor using surrogate optimization

The surrogate optimization is performed iteratively as follows:

1. Initialize system parameters, feasible power allocation values $p_i^{(0)}$ and convergence tolerance ϵ.
2. At iteration k, compute: $I_i^{(k)}$.
3. Construct the surrogate rate function.
4. Solve the optimization problem.
5. Check convergence:
6. Repeat until convergence is achieved.

The flowchart for the power allocation strategy is shown in Figure 2.

5. Results and Discussions

This section provides results and discussions of the present work. The outage probability as a function of transmit power for two users in a cluster-based NOMA system, comparing static and dynamic power allocation strategies, is shown in Figure 3. Since static power allocation allocates predefined power levels irrespective of channel conditions, it fails to adapt to real-time fading or interference. This often leads to poor reliability. Dynamic power allocation using surrogate optimization optimizes power levels based on instantaneous CSI, thereby enhancing user performance. In practical fading environments, it compensates for inter-user interference and varying channel quality.

Simulation results confirm that dynamic PA consistently outperforms static PA for both users across the entire transmitted power range. The outage probability under dynamic PA decreases rapidly with increasing transmitting power, reaching very low levels as 10^{-4} .This shows improvement in link reliability. Due to limited adaptability to varying channel conditions and inter-cluster interference, a static PA leads to consistently high outage probabilities, particularly for user 2, where the outage remains close to unity over a wide range of transmit powers. This highlights the inherent limitation of fixed power coefficients in NOMA systems.

The superior performance of dynamic PA is aided by surrogate optimization, which transforms the non-convex power allocation problem into a tractable form. It iteratively adjusts power coefficients to enhance SINR, mitigate inter-user interference, and satisfy QoS constraints. Consequently, the proposed approach achieved efficient resource allocation within the cluster, thereby reducing outage probability and improving overall system performance.

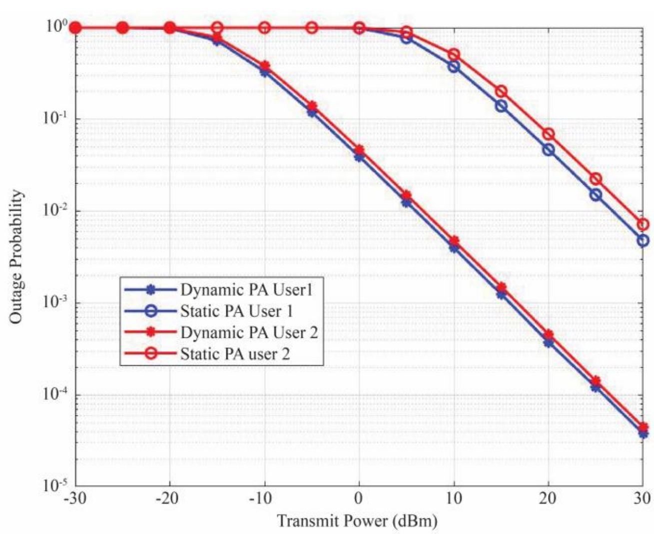

Fig. 3 Comparison of outage probability for static and dynamic power allocation in NOMA

The variation of cluster average data rate with respect to the power allocation coefficient α for dynamic PA, static PA, and OMA schemes is depicted in Figure 4. As α increases from 0.1 to 0.5, all three schemes exhibit a gradual improvement in data rate.

However, dynamic PA consistently outperforms the others, increasing from approximately 16.5 to 18 nats/s/Hz, while static PA improves from about 15.2 to 16.7 nats/s/Hz. In contrast, OMA shows significantly lower performance, rising only from around 1.8 to 2.1 nats/s/Hz. Dominance of dynamic PA across all values shows that optimization effectively fine-tunes power allocation and significantly enhances average data rate.

The performance gap widens as the power allocation factor increases, proving that dynamic PA smartly redistributes power to maintain both users' QoS requirements. Static PA provides suboptimal performance due to its inability to trade off between users optimally. OMA is inferior, as shown from simulation results, reinforcing that spectrum reuse in NOMA, especially with intelligent power control, is beneficial for future generations of wireless networks.

Figure 5 illustrates the individual data rates of two users versus transmit power for both dynamic and static power allocation schemes in NOMA. Dynamic PA adaptively adjusts power control based on instantaneous channel conditions, thereby maximising the sum rate and improving fairness. Static PA is not responsive to channel fluctuations because of fixed power coefficients, resulting in suboptimal user rates.

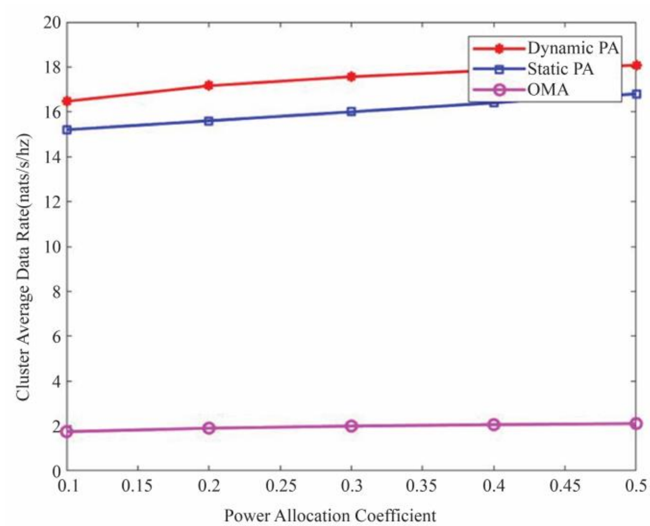

Fig. 4 Cluster average data rate with respect to power allocation

At low power levels (below 0 dBm), all users experience negligible rates due to poor SINR. Beyond 0–10 dBm, user rates increase significantly. Under dynamic PA, user 1 achieves a sharp rise from about 0.3 to 3.4 bps/Hz, while user 2 increases more moderately from around 0.2 to 1.7 bps/Hz. This indicates efficient power redistribution based on instantaneous channel conditions. In contrast, static PA achieves lower data rates for both users. User 1 reaches only about 0.85 bps/Hz and user 2 about 0.8 bps/Hz at 30 dBm. This proves that dynamic PA significantly enhances user-specific performance by adaptively allocating power. The stronger user benefits in this scheme while still improving the weaker user's rate, thereby achieving better overall system efficiency. It can be seen that increasing SNR benefits equally in all schemes. Adaptive power allocation in NOMA effectively exploits favourable channel conditions, resulting in enhanced spectral efficiency compared to both static allocation and conventional OMA.

Figure 6 presents an analysis of the variation of the cluster data rate with changes in the signal-to-noise ratio. As SNR increases, all schemes exhibit a steady rise in cluster rate due to improved signal quality.

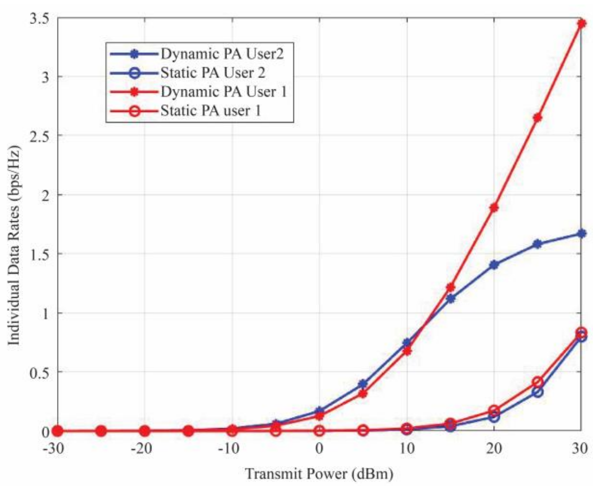

Fig. 5 Individual data rate versus transmit power

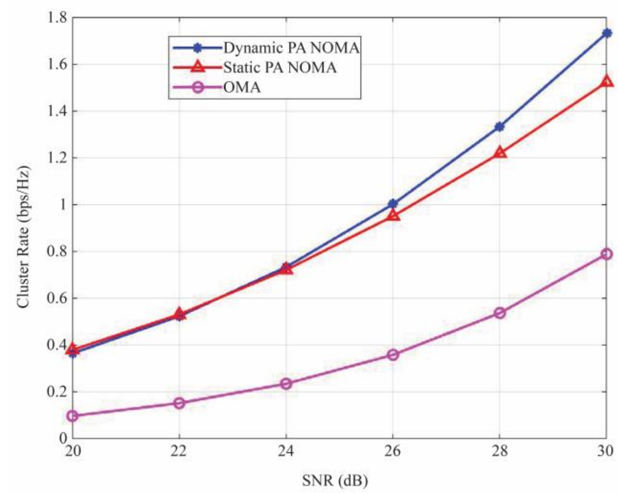

Fig. 6 Cluster data rate versus SNR (dB)

Dynamic PA consistently achieves the highest performance, increasing from about 0.38 to 1.75 bps/Hz, while static PA NOMA grows from approximately 0.4 to 1.55 bps/Hz.

OMA, in contrast, remains significantly lower, improving only from around 0.1 to 0.8 bps/Hz. Table 4 provides a consolidated result summary of the numerical gains explained in this section.

Table 4. Consolidated summary of results

Metric	Static PA	Proposed method-Surrogate + KKT
Outage probability at high Transmit power	Remains close to 10^{-2}	As low as 10^{-4}
Cluster average data rate (α = 0.1–0.5)	15.2 - 16.7 nats/s/Hz	16.5 – 18.0 nats/s/Hz
Individual rate, User 1 at 30 dBm	0.85 bps/Hz	3.4 bps/Hz
Individual rate, User 2 at 30 dBm	0.8 bps/Hz	1.7 bps/Hz
Cluster rate vs. SNR (upper end)	1.55 bps/Hz	1.75 bps/Hz

The performance gains reported above can be attributed to three specific mechanisms embedded in the proposed surrogate-KKT formulation. First, the accuracy of interference representation: because the surrogate rate function in Equation (10) is derived by first-order Taylor expansion of the true log-rate expression around the current operating point. It retains a tight local approximation of both intra- and inter-cluster interference at each iteration, rather than the fixed or partially-ignored inter-cluster term used in several convex-reformulation baselines [34, 38]. This tighter approximation allows the power update to react more precisely to the true interference environment, which directly explains the lower outage probability observed for User 2 in Figure 3, since User 2 is the user most exposed to residual interference. Second, optimality of the per-iteration update: because the surrogate objective is concave and the feasible set is convex, the resulting surrogate optimization problem is a convex optimization problem. Consequently, the KKT conditions provide the optimal solution of the surrogate sub-problem under the stated regularity conditions, unlike GA or SA-based schemes [44-47], which explore a discretised or randomly perturbed solution space and therefore converge to a near-optimal rather than exact solution of whatever sub-problem they are evaluating. Third, absence of approximation error from function learning: unlike RL-based schemes [50, 51], which approximate the power allocation policy using a learned function trained on a finite set of channel realisations and therefore carry generalisation error on unseen channel states, the proposed scheme re-derives its power update analytically from the instantaneous channel gains at every iteration, so its accuracy does not depend on the diversity or size of a training set. These three mechanisms jointly explain both the outage probability reduction to as low as 10^{-4} (Figure 3) and the approximately 8% cluster-rate gain over static PA (Figure 4). The surrogate model captures the true interference structure closely enough that the closed-form KKT solution operates near the true superior optimum, while incurring only the computational cost of solving a sequence of convex sub-problems rather than a search, training, or full numerical-solver procedure.

6. Conclusion

This paper addressed the non-convex power allocation problem, implemented through a regression-based surrogate optimization method in a clustered downlink NOMA system. Simulation results confirm that surrogate optimization effectively transforms the non-convex power allocation problem into a tractable form, enabling adaptive power control. This technique improves SINR, mitigates interference, and maximizes spectral efficiency in the NOMA system. Dynamic PA achieves a substantial reduction in outage probability as low as 10^{-4}, particularly at higher transmit power levels. From a throughput perspective, dynamic PA enhances the cluster average data rate by approximately 8% over static NOMA, and delivers nearly eight times higher performance compared to OMA, highlighting the advantage of non-orthogonal transmission combined with adaptive optimization. Similarly, dynamic PA achieves a substantial increase in individual user data rate over static PA at higher transmit powers. The proposed scheme ensures better fairness and efficient utilization of resources, offering a robust and scalable solution for enhancing both reliability and throughput. Given its low complexity and closed-form nature, the proposed framework is well suited for real-time deployment in dense, cluster-based 5G and Beyond 5G networks where CSI must be processed under tight latency constraints.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Funding Statement

No funding was received for the present work.

Acknowledgments

Author 1 and Author 2 contributed equally to this work.

References

[1] Konstantinos Samdanis, and Tarik Taleb, "The Road Beyond 5G: A Vision and Insight of the Key Technologies," *IEEE Network*, vol. 34, no. 2, pp. 135-141, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[2] Linglong Dai et al., "Non-Orthogonal Multiple Access for 5G: Solutions, Challenges, Opportunities, and Future Research Trends," *IEEE Communications Magazine*, vol. 53, no. 9, pp. 74-81, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[3] Yuanwei Liu et al., "Nonorthogonal Multiple Access for 5G and Beyond," *Proceedings of the IEEE*, vol. 105, no. 12, pp. 2347-2381, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[4] Mohammad Moltafet et al., "A New Multiple Access Technique for 5G: Power Domain Sparse Code Multiple Access (PSMA)," *IEEE Access*, vol. 6, pp. 747-759, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[5] Mohammed Abd-Elnaby et al., "NOMA for 5G and Beyond : Literature Review and Novel Trends," *Wireless Networks*, vol. 29, no. 4, pp. 1629-1653, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[6] Mojtaba Vaezi, Zhiguo Ding, and H. Vincent Poor, *Multiple Access Techniques for 5G Wireless Networks and Beyond*, Springer, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[7] Ying Lin et al., "Downlink Non-Orthogonal Multiple Access Power Allocation Algorithm Based on Double Deep Q Network for Ensuring User's Quality of Service," *Symmetry*, vol. 16, no. 12, pp. 1-16, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[8] Sara Norouzi, Benoit Champagne, and Yunlong Cai, "Joint Optimization Framework for User Clustering, Downlink Beamforming, and Power Allocation in MIMO NOMA Systems," *IEEE Transactions on Communications*, vol. 71, no. 1, pp. 214-228, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] MD Shipon Ali, Hina Tabassum, and Ekram Hossain, "Dynamic User Clustering and Power Allocation for Uplink and Downlink Non-Orthogonal Multiple Access (NOMA) Systems," *IEEE Access*, vol. 4, pp. 6325-6343, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[10] Zhiguo Ding et al., "A Survey on Non-Orthogonal Multiple Access for 5G Networks: Research Challenges and Future Trends," *IEEE Journal on Selected Areas in Communications*, vol. 35, no. 10, pp. 2181-2195, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[11] Zhiguo Ding et al., "On the Performance of Non-Orthogonal Multiple Access in 5G Systems with Randomly Deployed Users," *IEEE Signal Processing Letters*, vol. 21, no. 12, pp. 1501-1505, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[12] Minseok Choi, Joongheon Kim, and Jaekyun Moon, "Dynamic Power Allocation and User Scheduling for Power-Efficient and Delay-Constrained Multiple Access Networks," *IEEE Transactions on Wireless Communications*, vol. 18, no. 10, pp. 4846-4858, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[13] Mahmoud Aldababsa et al., "A Tutorial on Nonorthogonal Multiple Access for 5G and Beyond," *Wireless Communications and Mobile Computing*, vol. 2018, no. 1, pp. 1-24, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[14] Linglong Dai et al., "A Survey of Non-Orthogonal Multiple Access for 5G," *IEEE Communications Surveys & Tutorials*, vol. 20, no. 3, pp. 2294-2323, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[15] Jingjing Cui, Zhiguo Ding, and Pingzhi Fan, "A Novel Power Allocation Scheme under Outage Constraints in NOMA Systems," *IEEE Signal Processing Letters*, vol. 23, no. 9, pp. 1226-1230, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[16] Kankanala Kavitha, and Suseela Vappangi, “Performance Analysis of Novel User Pairing-Based Hybrid NOMA System with Fixed/Optimal Power Allocation Strategy,” *IEEE Access*, vol. 11, pp. 106037-106053, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[17] José Armando Oviedo, and Hamid R. Sadjadpour, “A Fair Power Allocation Approach to NOMA in Multiuser SISO Systems,” *IEEE Transactions on Vehicular Technology*, vol. 66, no. 9, pp. 7974-7985, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[18] Adarsh Ravi, and Preetam Kumar, “Optimality of NOMA Using Fair Power Allocation Policy for Wireless Communication Systems,” *Wireless Personal Communications*, vol. 145, pp. 451-464, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[19] Siyu Tao et al., “Performance Analysis of Gain Ratio Power Allocation Strategies for Non-Orthogonal Multiple Access in Indoor Visible Light Communication Networks,” *EURASIP Journal on Wireless Communications and Networking*, vol. 2018, no. 1, pp. 1-14, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[20] Xiaoke Zhang et al., “User Grouping and Power Allocation for NOMA Visible Light Communication Multi-Cell Networks,” *IEEE Communications Letters*, vol. 21, no. 4, pp. 777-780, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[21] Hanaa Marshoud et al., “Non-Orthogonal Multiple Access for Visible Light Communications,” *IEEE Photonics Technology Letters*, vol. 28, no. 1, pp. 51-54, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[22] Xian Zhong, Pu Miao, and Xiaoqing Wang, “Enhanced Gain Difference Power Allocation for NOMA-Based Visible Light Communications,” *Electronics*, vol. 13, no. 4, pp. 1-17, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[23] Ibrahim A. Elewah, Faezah Jasman, and Sha Shiong Ng, “Analysis on the Performance of Normalised Gain Difference Power Allocation for MIMO NOMA-based VLC,” *International Journal of Nanotechnology*, vol. 19, no. 2-5, pp. 113-115, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[24] Mohammed Al-Imari et al., “Uplink Non-Orthogonal Multiple Access for 5G Wireless Networks,” *2014 11th International Symposium on Wireless Communications Systems (ISWCS)*, Barcelona, Spain, pp. 781-785, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[25] Zhiguo Ding, Mugen Peng, and H. Vincent Poor, “Cooperative Non-Orthogonal Multiple Access in 5G Systems,” *IEEE Communications Letters*, vol. 19, no. 8, pp. 1462-1465, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[26] Jinho Choi, “Non-Orthogonal Multiple Access in Downlink Coordinated Two-Point Systems,” *IEEE Communications Letters*, vol. 18, no. 2, pp. 313-316, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[27] Zhiguo Ding, Fumiyuki Adachi, and H. Vincent Poor, “The Application of MIMO to Non-Orthogonal Multiple Access,” *IEEE Transactions on Wireless Communications*, vol. 15, no. 1, pp. 53-552, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[28] Zhiguo Ding, Pingzhi Fan, and H. Vincent Poor, “Impact of User Pairing on 5G Nonorthogonal Multiple-Access Downlink Transmissions,” *IEEE Transactions on Vehicular Technology*, vol. 65, no. 8, pp. 6010-6023, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[29] Yaru Fu et al., “Subcarrier and Power Allocation for the Downlink of Multicarrier NOMA Systems,” *IEEE Transactions on Vehicular Technology*, vol. 67, no. 12, pp. 11833-11847, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[30] Jun Li et al., “Power Allocation and User Grouping for NOMA Downlink Systems,” *Applied Sciences*, vol. 13, no. 4, pp. 1-13, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[31] Xinli Ma et al., “Power Allocation for Downlink of Non-Orthogonal Multiple Access System via Genetic Algorithm,” *International Conference on 5G for Future Wireless Networks*, pp. 459-470, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[32] Zheng Yang et al., “Outage Performance for Dynamic Power Allocation in Hybrid Non-Orthogonal Multiple Access Systems,” *IEEE Communications Letters*, vol. 20, no. 8, pp. 1695-1698, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[33] Zheng Yang et al., “A General Power Allocation Scheme to Guarantee Quality of Service in Downlink and Uplink NOMA Systems,” *IEEE Transactions on Wireless Communications*, vol. 15, no. 11, pp. 7244-7257, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[34] Xunan Li, Chong Li, and Ye Jin, “Dynamic Resource Allocation for Transmit Power Minimization in OFDM-Based NOMA Systems,” *IEEE Communications Letters*, vol. 20, no. 12, pp. 2558-2561, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[35] Shiguo Wang, Shu Cao, and Rukhsana Ruby, “Optimal Power Allocation in NOMA-based Two-Path Successive AF Relay Systems,” *EURASIP Journal on Wireless Communications and Networking*, vol. 2018, pp. 1-12, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[36] Rummi Sirait, Wibowo Hardjawana, and Gunawan Wibisono, “Performance of Downlink NOMA for a Massive IoT Network Over a Nakagami- m Fading Channel With Optimized Power Allocation,” *IEEE Access*, vol. 11, no. 6, pp. 67779-67790, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[37] Wali Ullah Khan et al., “Spectral Efficiency Optimization for Next Generation NOMA-Enabled IoT Networks,” *IEEE Transactions on Vehicular Technology*, vol. 69, no. 12, pp. 15284-15297, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[38] M. K. Noor Shahida, Rosdiadee Nordin, and Mahamod Ismail, “An Improved Water-Filling Algorithm based on Power Allocation in Network MIMO,” *Telecommunication Systems*, vol. 75, no. 4, pp. 447-460, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[39] Ninghao Zhou, Jinfeng Hu, and Jia Hou, “Research on Energy Efficiency of NOMA–SWIPT Cooperative Relay Network Using GS-DinkelBach Algorithm,” *Sensors*, vol. 21, no. 17, pp. 1-18, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[40] Fang Fang et al., "Joint User Scheduling and Power Allocation Optimization for Energy-Efficient NOMA Systems with Imperfect CSI," *IEEE Journal on Selected Areas in Communications*, vol. 35, no. 12, pp. 2874-2885, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[41] Jia Shao, Cong Li, and Taotao Yan, "Power Allocation with QoS and Max-Min Fairness Constraints for Downlink MIMO-NOMA System," *IEICE Transactions on Communications*, vol. 106, no. 12, pp. pp. 1411-1417, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[42] Lou Salaün et al., "Weighted Sum-Rate Maximization in Multi-Carrier NOMA with Cellular Power Constraint," *IEEE INFOCOM 2019 - IEEE Conference on Computer Communications*, Paris, France, pp. 451-459, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[43] Ming Zeng, and Viktoria Fodor, "Sum-Rate Maximization under QoS Constraint in MIMO-NOMA Systems," *2018 IEEE Wireless Communications and Networking Conference (WCNC)*, Barcelona, Spain, pp. 1-6, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[44] Ömer Faruk Gemici et al., "Resource Allocation for NOMA Downlink Systems : Genetic Algorithm Approach," *2017 40th International Conference on Telecommunications and Signal Processing (TSP),* Barcelona, Spain, pp. 114-118, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[45] Seda Kirtay, Veysel Gokhan Bocekci, and Kazim Yildiz, "Genetic Algorithm Based Approach f or Optimization of Fair Power Allocation in Pd-NOMA," *Technical Journal*, vol. 32, no. 3, pp. 948-957, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[46] Osama Abuajwa, Mardeni Bin Roslee, and Zubaida Binti Yusoff, "Simulated Annealing for Resource Allocation in Downlink NOMA Systems in 5G Networks," *Applied Sciences*, vol. 11, no. 10, pp. 1-16, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[47] Botao Yang, Ye Liu, and Chung Shue Chen, "Uplink Scheduling in a NOMA-enabled Single-Cell Wireless Network Using Simulated Annealing," *2023 21st International Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks (WiOpt)*, Singapore, pp. 485-492, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[48] Sunkaraboina Sreenu, and Naidu Kalpana, "Innovative Power Allocation Strategy for NOMA Systems by Employing the Modified ABC Algorithm," *Radioengineering*, vol. 31, no. 3, pp. 312-322, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[49] Fei Liu, and Marina Petrova, "Dynamic Power Allocation for Downlink Multi-Carrier NOMA Systems," *IEEE Communications Letters*, vol. 22, no. 9, pp. 1930-1933, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[50] Shaomin Zhang et al., "A Dynamic Power Allocation Scheme in Power-Domain NOMA using Actor-Critic Reinforcement Learning," *2018 IEEE/CIC International Conference on Communications in China (ICCC)*, Beijing, China, pp. 719-723, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[51] Hoang Thi Huong Giang et al., "Hybrid NOMA/OMA-Based Dynamic Power Allocation Scheme Using Deep Reinforcement Learning in 5G Networks," *Applied Sciences*, vol. 10, no. 12, pp. 1-19, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[52] Sunil Chinnadurai, Poongundran Selvaprabhu, and Moon Ho Lee, "A Novel Joint User Pairing and Dynamic Power Allocation Scheme in MIMO-NOMA System," *2017 International Conference on Information and Communication Technology Convergence (ICTC)*, Jeju, Korea (South), pp. 951-953, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[53] Fei Liu, and Marina Petrova, "Performance of Dynamic Power and Channel Allocation for Downlink MC-NOMA Systems," *IEEE Transactions on Wireless Communications*, vol. 19, no. 3, pp. 1650-1662, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[54] Bhaskara Narottama, and Soo Young Shin, "Dynamic Power Allocation for Non-Orthogonal Multiple Access with User Mobility," *2019 IEEE 10th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON)*, Vancouver, BC, Canada, pp. 442-446, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[55] Cinnie Hsiung et al., "Dynamic User Pairing and Power Allocation for Throughput Maximization in NOMA Systems," *2019 IEEE International Conference on Communications Workshops (ICC Workshops),* Shanghai, China, pp. 1-6, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[56] Zahra Amirifar, and Jamshid Abouei, "The Dynamic Power Allocation to Maximize the Achievable Sum Rate for Massive MIMO-NOMA Systems," *IET Communications*, vol. 16, no. 17, pp. 2036-2044, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[57] Osama Abuajwa, and Sufian Mitani, "Dynamic Resource Allocation for Energy-Efficient Downlink NOMA Systems in 5G Networks," *Heliyon*, vol. 10, no. 9, pp. 1-16, 2024. [CrossRef] [Google Scholar] [Publisher Link]