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Review Article

Evolution of Power Allocation Techniques in NOMA: Advancing 5G Toward 6G Networks

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Abstract *- The transition of 5G and beyond wireless networks toward intelligence-driven and autonomous operation has revitalized strong interest in Non-Orthogonal Multiple Access (NOMA) as an efficient multiple access framework. Power allocation critically governs NOMA performance, directly impacting throughput, user fairness, and SIC effectiveness. This survey presents a focused review of power allocation strategies in NOMA, with emphasis on the progression from static and optimization-based dynamic schemes to data-driven Artificial Intelligence (AI) and Machine Learning (ML) driven approaches. In contrast to conventional strategies that require instantaneous channel state information and iterative optimization, AI/ML techniques enable adaptive, scalable, and low-latency decision-making in highly dynamic and nonconvex environments. Recent advances in reinforcement learning and deep learning for NOMA power control are discussed, highlighting key challenges like imperfect CSI, inter-cluster interference, and distributed learning constraints. This survey provides a concise AI-centric analysis and identifies promising directions for a practical learning-driven NOMA power allocation framework for future wireless networks. A consolidated, critically comparative analysis of NOMA power allocation that bridges the gap between 5G practice and 6G imperatives is also presented in this survey.*

Keywords *- AI/ML Based Power Allocation, Multiple Access Techniques, Noma, Optimization, Static And Dynamic Power Allocation, 6G.*

1. Introduction

Non-Orthogonal Multiple Access (NOMA) has emerged as a promising multiple access framework for Fifth Generation (5G) and beyond wireless networks owing to its ability to support massive connectivity, enhanced spectral efficiency, and accommodate heterogeneous Quality of Service (QoS) requirements[1],[2]. The performance gain of NOMA is intrinsically governed by the effectiveness of the power allocation strategy[3], which determines the degree of signal superposition and directly impacts interference mitigation, Successive Interference Cancellation (SIC) feasibility, and user rate distribution[4],[5].

An appropriately designed power allocation scheme ensures sufficient power differentiation for reliable SIC while balancing system throughput, energy efficiency, and user fairness[6],[7]. Hence, power allocation not only functions as a supporting mechanism, but a core enabler that governs both the achievable performance and practical viability of NOMA in future wireless communication systems[8],[9],[10]. This necessitates the development of sophisticated and adaptive power allocation algorithms capable of efficiently navigating these competing objectives to realize the full performance potential of NOMA systems[11],[12]. Accordingly, practical NOMA deployments increasingly adopt advanced optimization frameworks, iterative solution techniques, as well as heuristic and learning-based approaches to attain near-optimal performance with manageable computational complexity and real-time operational feasibility[13],[14].

Power allocation strategies in NOMA systems can be categorized into static and dynamic schemes based on their ability to adapt to channel and network variations[15],[16]. Static schemes employ fixed or long-term channel information, offering low computational complexity, but exhibit limited adaptability and suboptimal performance[17] under a dynamic wireless environment. In contrast, dynamic power allocation adaptively updates power coefficients using instantaneous CSI, user-specific QoS requirements, and interference conditions. This is typically achieved through optimization-based formulations that aim at maximization of performance objectives such as sum rate, energy efficiency, or fairness under SIC and power constraints[18]. This inherent trade-off between low complexity implementation and performance optimality motivates the development of efficient dynamic power allocation strategies that balance performance gain and real-time feasibility in NOMA systems[19],[20].

The increasing complexity and highly dynamic operational characteristics of NOMA networks have rendered conventional optimization-based power allocation increasingly inadequate, thereby driving the Interest of Artificial Intelligence (AI) and Machine Learning (ML) [21] enabled solutions. Practical deployments with rapidly varying channels, user mobility, interference uncertainty, and heterogeneous QoS demands, learning-based methods can infer near-optimal power policies directly from data with low latency and reduced reliance on perfect CSI[22]. Consequently, AI and ML emerge as key enablers for scalable, low-latency, and robust power allocation in NOMA systems, making them well suited paradigm for 5G and beyond wireless networks requiring real-time adaptability.

Despite the extensive research conducted on power allocation techniques in NOMA, spanning static fixed power allocation, optimization-based dynamic techniques, and more recently AI/ML-driven approaches, a consolidated, critically comparative analysis of NOMA power allocation techniques that bridges the gap between 5G practice and 6G imperatives is conspicuously absent. Specifically, the following research gaps have been identified:

- No unified framework systematically contrasts static, dynamic, and AI/ML power allocation techniques across a consistent set of performance metrics, including complexity, fairness, CSI requirement, scalability, and suitability for 6G applications.
- Existing surveys inadequately address the challenges associated with transitioning from 5G-centric optimization models to 6G-compliant learning-based architectures, including THz propagation, RIS-assisted environments, and federated edge intelligence.
- The interplay between SIC imperfection, imperfect CSI, and power allocation design, which is critical for practical deployments, is rarely examined across all three paradigms.
- Critical evaluation of AI/ML methods with respect to training overhead, convergence guarantees, and deployment feasibility on resource-constrained network devices is lacking.

Motivated by these research gaps, this survey provides a structured, critical, and comparative review of all major NOMA power allocation paradigms, synthesizing their design principles, quantified trade-offs, and suitability for next-generation networks. The fundamental research problem addressed in this work is how the power allocation should be designed in NOMA systems to effectively balance the conflicting demands of computational tractability, real-time adaptability, SIC reliability, user fairness, and energy efficiency while meeting the demands of 6G networks characterized by extreme heterogeneity, pervasive intelligence, and massive connectivity. Addressing this question necessitates a holistic review that not only documents existing approaches but also critically analyses their relative merits, failure modes, and evolution trajectory.

The main contributions of this survey are summarized as follows:

- Comprehensive review of static power allocation: This survey provides a structured and critical review of conventional static power allocation schemes for NOMA, emphasizing their fundamental design principles and low implementation complexity, while exposing their inherent limitations in terms of adaptability, user fairness, and spectral efficiency. By considering static allocation as a baseline reference, this analysis systematically reveals its performance bottlenecks when operating under dynamic channel variations and interference-intensive network environments.
- Systematic analysis of dynamic power allocation techniques: This paper provides a comprehensive review of optimization-based dynamic power allocation methods, encompassing iterative, convexified, and heuristic approaches. Associated trade-offs among sum-rate maximization, energy efficiency, fairness, and computational complexity are evaluated, along with particular emphasis on SIC feasibility and QoS constraints in multi-user NOMA environments.
- Integration of AI and ML based power allocation frameworks: Recognizing the limitations of analytical optimization, this survey reviews and systematically categorizes AI and ML-driven power allocation strategies, including supervised learning, reinforcement learning, and deep learning approaches. The review further highlights how learning-based methods effectively mitigate non-convexity, scalability, and real-time adaptation challenges, thereby using AI/ML frameworks to bridge the gap between the low complexity of static schemes and the performance optimality of dynamic power allocation in NOMA systems.
- Unified perspective and research outlook: This survey synthesizes and contrasts static, dynamic, and AI/ML-based power allocation paradigms, identifying key open research challenges and highlighting future directions toward a robust, low-complexity, and scalable allocation framework tailored for next-generation NOMA-enabled wireless networks.
- 6G-Centric Forward Analysis: Existing surveys largely treat NOMA power allocation within the context of the

5G problem. This survey explicitly maps each paradigm's limitations against the 6G requirements.

The remainder of this article is organized as follows: Sections 2 and 3 review static power allocation schemes and dynamic power allocation schemes in NOMA, respectively. Section 4 provides AI/ML-driven approaches with critical analysis. Section 5 presents comparative discussion, research gap analysis, and future directions. Section 6 concludes the survey.

2. Static Power Allocation Schemes

Static power allocation employs 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. However, it is the lack of adaptability to time-varying channels, interference dynamics, and heterogeneous QoS demands that often leads to inefficient spectrum utilization, rate imbalance, and degraded SIC performance. Consequently, static schemes are mainly suitable for simplified or low-mobility scenarios, motivating the classifications discussed subsequently.

2.1. Fixed Power Allocation (FPA)

FPA represents a canonical static power-control approach in NOMA, wherein predetermined power coefficients, which remain constant over time, are assigned to users. Users are ordered based on long-term channel statistics, such as average channel gains[23], and power allocation follows the SIC decoding hierarchy. Its reliance on average CSI results in low signalling and computational complexity while ensuring fairness under outage-based constraints, and it consistently outperforms OMA in terms of outage probability and user support for a given transmit power.

Extending this static approach, hybrid frameworks such as [24] jointly optimize user pairing and power allocation under perfect and imperfect SIC to achieve higher spectral efficiency and sum rate, along with reduced outage. The distributed design in [25] further enhances performance in heterogeneous NOMA networks but reveals scalability limitations due to fixed power coefficients, complex interference management, and dynamic SIC requirements, thereby motivating needs of adaptive power-allocation strategies.

2.2. Gain Ratio Power Allocation (GRPA)

GRPA enhances fairness and sum-rate in NOMA by allocating power using the ratio of each user's channel gain to that of the strongest user, introducing limited channel awareness while preserving the low complexity of static schemes. In [26] and [27], GRPA-based location-aware power allocation schemes for VLC NOMA improve data rate, spectral efficiency, and inter-cell interference management over OMA, but their static channel ratio dependence and iterative location-sensitive optimization limit adaptability and scalability in dynamic environments.

In [28] and [29], 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.

2.3. Normalized Gain Difference Power Allocation (NGDPA)

Normalized Gain Difference Power Allocation allocates power using normalized channel gain differences in indoor MIMO PD-NOMA VLC systems. The authors in [30] achieved enhanced sum-rate gain over GRPA with low complexity. By normalizing the gain difference, overall sum rate efficiency is improved because power is assigned in a way that better reflects the actual channel disparities among users.

2.4. Fair-NOMA Approach

Fair-NOMA ensures that each user attains at least its OMA capacity by analytically defining a feasible power-allocation region [31] that enhances both individual and sum rates, achieving better ergodic sum-rate gains at high SNR and enhanced weak-user outage performance without requiring additional transmit power. The fair power allocation scheme in [32] guarantees each NOMA user at least its OMA capacity based on inter-user channel gain differences, achieving simultaneous improvements in individual and sum capacities with increasing SNR and reduced outage probability, thereby offering a power-efficient and fairness-oriented enhancement over conventional NOMA.

Fair-NOMA has been extended to K-user systems in [33], where it analytically proposes an optimal downlink multi-user NOMA power-allocation strategy that maximizes sum rate, with simulations confirming superior spectral efficiency and fairness over OMA, fixed-NOMA, and benchmark methods.

Table 1 summarizes the static power allocation schemes and performance schemes implemented for NOMA in the 5G scenario. Despite its low complexity and implementation simplicity, static power allocation in NOMA cannot adapt to instantaneous channel variations, user mobility, or dynamic interference, resulting in suboptimal spectral efficiency and degraded SIC reliability under CSI uncertainty.

These limitations become more pronounced in heterogeneous and dense multi-user scenarios, where fixed power coefficients fail to ensure fairness, QoS, and effective interference management, thereby constraining overall system performance.

Table 1. Comparative summary of static power allocation techniques and performance objectives in NOMA

Ref.	System Model	PA Strategy	Fundamental Objective	Advantages	Limitations
[23]	Downlink NOMA	FPA	Throughput, fairness	Very low complexity, easy implementation	Interference dynamics are ignored
[24]	Hybrid NOMA	FPA	Sum-rate, fairness	Improved spectral efficiency, reduced outage	Requires optimal pairing
[25]	NOMA HetNet	FPA	Spectral efficiency	SIC-feasible, Reduced outage	Increased computational complexity
[26]	Indoor VLC-NOMA	Enhanced GRPA	Sum rate	Better SIC efficiency, higher throughput	Channel-static, limited adaptivity
[27]	Multi-cell VLC-NOMA	GPRA	Sum-rate / Min-rate	Accounts for residual SIC interference	Iterative, location-dependent
[28]	VLC-NOMA	GRPA and optical tuning	Spectral efficiency	Improved BER, supports more users	Requires optical optimization
[29]	MIMO VLC-NOMA	EGDPA	Sum rate, BER	Strong interference mitigation, fairness	Higher complexity, single-cell focus
[30]	MIMO VLC-NOMA	NGDPA	Sum rate	Up to 29.1% gain over GRPA, low complexity	Limited adaptability
[31]	Downlink NOMA	Fair-NOMA	Fairness, Spectral efficiency	Each user ≥OMA capacity	Idealized assumptions
[32]	Downlink NOMA	Fair-NOMA	Capacity and reliability	Lower outage, scalable fairness	Requires accurate channel ordering
[33]	Multi-user NOMA	Fair-NOMA	Spectral efficiency	Outperforms OMA and fixed-NOMA	Centralized optimization, CSI dependent

3. Dynamic Power Allocation (DPA)

In contrast to static schemes, dynamic power allocation adapts transmit power to instantaneous CSI, user-specific requirements, and interference levels, enabling efficient interference management, reliable SIC, and exploitation of channel diversity. This adaptability yields higher spectral efficiency, sum-rate, and fairness under heterogeneous QoS requirements, making dynamic schemes well suited solution for dense and time-varying NOMA environments despite increased complexity. The following section gives a detailed review of different dynamic power allocation schemes in NOMA.

3.1. Convex Optimization

Convex optimization provides a framework for dynamic power allocation in NOMA systems by enabling globally optimal, low complexity solutions under instantaneous CSI and interference constraints. The authors in [34] formulated power allocation for dynamic OFDM NOMA and iteratively update subcarriers using a deletion algorithm to outperform OFDMA and static NOMA under perfect CSI. Pattern Division Multiple Access (PDMA) is introduced in [35], which utilizes fixed power domain patterns to enable high overload capability and near OMA reliability at low optimization complexity.

Uplink and IoT-oriented designs in [36] and [37] exploit CSI-aware convex power control and KKT-based optimization combined with matching algorithms to enhance effective capacity, delay performance, spectral efficiency, and energy efficiency over conventional NOMA and OMA. Delay-critical and interference-limited scenarios are addressed in [38] and [39], where quasi-convex latency minimization and fractional interference modelling with KKT-based updates achieve significant delay reduction and near-centralized performance in WPT-enabled IIoT (Industrial Internet of Things) and HetNet deployments.

For mobility and relay-assisted systems, [40] decomposes UAV-assisted NOMA throughput maximization into convex power control and trajectory subproblems, while [41] derives closed-form KKT-based power coefficients for two-path AF relay NOMA to improve spectral efficiency. Massive IoT and dense network extensions in [42] and [43] adopt convex optimization and SQP-based power control to mitigate imperfect SIC and scalability challenges, providing notable capacity and spectral-efficiency gains.

Water filling-based convex formulations support multi-carrier and clustered NOMA designs in [44] and [45], where Logarithmic Convexification (LC), virtual-FDMA mappings, iterative and distributed water filling, and proportional fair scheduling enable low-complexity closed-form or near optimal solutions. Improved sum rate, fairness, outage, and energy efficiency is the highlight of the system, but gain is diminished with increased cluster size and SIC complexity.

The study in [46] examines a cooperative NOMA SWIPT relay network with time-division resource allocation and applies a generalized Dinkelbach algorithm to maximize energy efficiency in both direct and cooperative modes. The system achieved fast convergence and notable EE gains, but suffers from increased complexity. Furthermore, [47] explores covert rate maximization in active RIS-aided MISO-NOMA systems by jointly optimizing power allocation and transmit/reflective beamforming. A penalized Dinkelbach approach enforces rank-one constraints and delivers substantial performance improvement compared with passive RIS-based schemes.

Dynamic frameworks grounded on Lyapunov drift theory in [48] enhance energy efficiency by converting long-term Energy Efficiency (EE) objectives into per-slot scheduling and power allocation decisions, thereby ensuring queue stability and low delay for heterogeneous traffic. Similarly, Dinkelbach based dual optimization and successive convex approximation in [49] provide computationally efficient solutions to inherently nonconvex EE maximization problems in uplink and downlink NOMA, achieving user-centric and priority-aware energy efficient operation. Table 2 provides a summary of various convex optimization-based dynamic power allocation in NOMA.

Table 2. Convex optimization techniques associated with dynamic power allocation in NOMA

Ref	Scenario	Optimization Objective	Key Techniques	Major Advantages	Disadvantages
[34]	Downlink OFDM-NOMA	Minimize total transmit power under QoS	Convexification, deletion-based joint subcarrier power updation	Significant power reduction, outperforms both OFDMA and static NOMA	Requires perfect CSI, Sensitive to SIC ordering, and higher complexity
[35]	PDMA	Throughput and overload support	Pattern matrices, SIC with BP/Turbo-BP	Supports up to 300% overload, low optimization overhead, robust grant-free access	Static power levels, limited adaptability
[36]	Uplink NOMA	Maximize effective capacity with delay QoS	Effective capacity theory, convex optimization, KKT	Improved throughput, delay, and fairness, closed-form power control	Depends on accurate CSI and delay modelling
[37]	D2D-enabled Uplink NOMA	Maximize EE and throughput with QoS	KM matching, KKT-based power allocation	Gains in EE, SE, and throughput over OMA/NOMA	Centralized matching overhead
[38]	Relay-assisted NOMA-WPT IIoT	Minimize end-to-end delay	Quasi-convex reformulation, KKT	~30.77% latency reduction, suitable for IIoT	Higher algorithmic complexity
[39]	Downlink HetNet NOMA	Joint clustering and resource allocation	Multipartite matching, KKT-based decomposition	Near-centralized performance, low signalling	Imperfect SIC, Degradation in performance with high SIC errors
[40]	UAV-assisted NOMA Downlink	Maximize throughput	KKT power control, auction-based trajectory planning	High task completion rate, low complexity vs exhaustive search	UAV mobility assumptions
[41]	Two-path AF Relay NOMA	Rate maximization, bandwidth minimization	Dual decomposition, KKT, convex optimization	Higher throughput and SE than equal PA	Assumes accurate channel knowledge

[41]	Massive IoT Downlink NOMA	Maximize channel capacity	Lagrangian, KKT closed-form PA	Improved capacity and outage vs OMA/static NOMA	Imperfect SIC
[43]	NOMA-enabled IoT	Maximize spectral efficiency	Heuristic FB assignment, SQP, KKT benchmark	High SE gains, scalable for dense IoT	Heuristic suboptimality
[44]	Multi-carrier / Hybrid NOMA	Sum-rate, EE maximization	Logarithmic water-filling, Dinkelbach	Low complexity global optimum, virtual FDMA model	Cluster head-centric allocation
[45]	LTE-A / NetMIMO	ICI mitigation, throughput, fairness	LC-IWF and Net MIMO	Up to 20–25% gain, large power and complexity reduction	LTE-A centric assumptions
[46]	Cooperative NOMA–SWIPT	EE maximization	Time-division resource allocation, EE optimized for direct and cooperative modes.	High EE gains, low complexity, accurate convergence	Iterative overhead in dense networks
[47]	Active RIS-aided MISO-NOMA	Covert rate maximization	Problem decoupling, rank-1 constrained optimization	Significant covert-rate improvement	High computational overload
[48]	Downlink NOMA	Time-average EE maximization	Lyapunov drift, slot-wise optimization	Superior EE, better stability	Requires queue-state awareness
[49]	Uplink and Downlink NOMA	Maximize weighted sum EE	Dinkelbach dual, SCA	Higher EE and user-centric gains	Convergence time for SCA

Joint optimization of user clustering and power allocation is critical for fully exploiting NOMA gains but leads to mixed integer, NP-hard problems that are infeasible for large-scale systems. Several low-complexity frameworks have been proposed that decouple matching-based user channel assignment from analytically optimal power allocation and highlight the limits of static optimization.

In [50] authors proposed the SWEET algorithm for uplink NOMA-IoT, which jointly optimizes clustering, channel assignment, and power control using SIC feasibility-aware cluster restructuring to minimize channel usage under heterogeneous QoS, but its complexity increases in dense IoT deployments.

A joint user pairing, channel assignment, and power allocation framework for NOMA-based cognitive radio networks is discussed in [51], convexifying the nonconvex sum rate maximization problem and solving it through dual decomposition with closed-form power coefficients, achieving high spectral efficiency at the expense of iterative complexity.

Addressing challenges of energy-efficient resource management, [52] presents a dynamic joint user scheduling and power allocation scheme for downlink NOMA under imperfect CSI conditions. The study transformed a probabilistic nonconvex formulation into a deterministic iterative solution, improving energy efficiency and outage performance while facing scalability challenges due to CSI sensitivity. Extending Dinkelbach-based designs to high-frequency systems, [53] proposes a two-layer Dinkelbach alternating optimization framework for joint power allocation and power splitting in SWIPT-enabled mm Wave beam space MIMO-NOMA, delivering significant improvements in energy efficiency and sum rate performance over benchmark schemes.

In SWIPT-enabled NOMA [54] and multi-cluster MIMO-NOMA systems [55], joint optimization of power allocation, time-switching, and user clustering, often using Dinkelbach transformation, Lagrangian methods, or closed-form water-filling solutions, yields significant EE gains over OMA and equal power NOMA under practical QoS constraints.

For D2D-enabled NOMA, [56] proposes a Distributed Decision Making (DDM) based joint resource-block and power allocation scheme that enhances D2D throughput and spectral efficiency while preserving cellular QoS, but with high computational overhead in large networks. Authors in

[57] employed Nash bargaining and hedonic coalition game models for joint clustering and power allocation in uplink MC-NOMA, attaining near-optimal throughput and improved fairness under D2D interference with significantly lower complexity compared to exhaustive optimization. Table 3 provides an insight into the joint optimization techniques that were discussed in the section above.

Table 3. Joint optimization techniques and performance objectives in NOMA

Ref.	System Scenario	Optimization Objective	Jointly Optimized Variables	Key Techniques /Algorithms	Advantages	Limitations
[50]	Uplink NOMA-IoT	Minimize channel usage under QoS	Clustering, channel assignment, and power allocation	SWEET algorithm, SIC-feasibility-based iterative updates	Reduced channel consumption, improved QoS satisfaction, and scalable clustering	Higher computational complexity, limited efficiency in ultra-dense IoT
[51]	NOMA-based Cognitive Radio	Sum-rate maximization under CR constraints	User pairing, channel assignment, and power allocation	Convexification, dual decomposition, closed-form PA	Superior sum-rate, effective NOMA–CR integration	Iterative overhead, limited scalability in dense CR networks
[52]	Downlink NOMA (Imperfect CSI)	Energy-efficiency maximization	User scheduling, power allocation	Deterministic reformulation, iterative optimization	Supports multi-user multiplexing, improved EE, and outage	CSI sensitivity, iterative overhead limits scalability
[53]	MIMO NOMA with SWIPT	EE maximization	Two-layer iterative framework for power allocation and splitting	Two-layer Dinkelbach–alternating optimization framework	Fast convergence, strong EE, and sum-rate gains	Requires accurate CSI, iterative complexity
[54]	SWIPT-enabled Downlink NOMA	Maximize EE under rate and energy constraints	Dinkelbach, Lagrangian dual, time-switching optimization	Joint power and time-switching optimization	Significant EE gains vs OMA/NOMA	Increased algorithm complexity
[55]	Multi-cluster MIMO-NOMA	Maximize EE with QoS	Closed-form PA, water-filling, admission control	Static EE-optimal PA with user admission	Improved EE and user admission	No dynamic adaptation
[56]	D2D-enabled NOMA	Maximize D2D throughput with cellular QoS	RB assignment, SIC order, power allocation	Differential evolution, SCA, heuristic search	High D2D rate and spectral efficiency gains	High complexity, poor scalability for large networks
[57]	Uplink MC-NOMA with D2D interference	Fair throughput maximization	User clustering, power allocation	Nash bargaining game, hedonic coalition game, KKT	Near-optimal throughput, improved fairness, fast convergence	Game theoretic iteration overhead

3.2. Max-min Fairness (MMF) Optimization

Max Min Fairness (MMF) optimization in NOMA focus to maximize the minimum achievable user rate, thereby protecting the worst served users and ensuring equitable resource allocation under shared spectrum transmission. Under instantaneous CSI, MMF-based power allocation formulations solved using KKT conditions and bisection methods [58] provide significant enhancement in edge user performance and fairness compared with conventional MIMO-NOMA and sum rate-oriented designs. Dynamic MMF frameworks in [59] jointly optimize power allocation, precoding, and subcarrier assignment using tools such as digital precoding, dynamic programming, and water-filling. It achieves substantial gains in minimum user rate and fairness in multi-carrier, beam space, and high mobility NOMA scenarios.

In multi-carrier NOMA [60], MMF-oriented resource allocation reforms tractable dynamic programming-based user selection and gradient-based power control, achieving near-optimal spectral efficiency with manageable computational complexity. For high mobility scenarios, OTFS-NOMA-based MMF [61] schemes employ optimal subcarrier matching and water-filling power allocation to enhance fairness and spectral efficiency beyond conventional OFDMA jointly.

Cross-cluster and joint resource allocation strategies in [62] effectively balance fairness and spectral efficiency in NOMA by guaranteeing weak-user QoS while maintaining competitive system throughput. Table 4 provides a summary of MMF Optimization in Dynamic Power Allocation NOMA.

Table 4. MMF optimization techniques and performance objectives in NOMA

Ref.	**System Model**	**Optimization Objective**	**Key Techniques / Algorithms**	**Main Contributions**	**Outcomes**	**Limitations**
[58]	Downlink MIMO-NOMA	Max–min fairness (edge users)	KKT conditions, bisection search, instantaneous CSI	Users are partitioned into head and edge users	Improved edge-user throughput and fairness while meeting head-user QoS	Requires accurate CSI, iterative convergence overhead
[59]	Beam space MIMO-NOMA	Maximize the minimum user rate	Alternating optimization, semidefinite relaxation, bisection-based search	Joint optimization of digital precoding and power allocation under inter-/intra-beam interference	Improvement in the minimum rate and robustness over fixed or sum rate schemes	Higher computational complexity due to SDR
[60]	Downlink Multi-carrier NOMA	Weighted sum-rate maximization	Dynamic programming, projected gradient descent	Decomposition of NP-hard problem into user selection and power control, adaptive user–subcarrier mapping	Near-optimal sum rate with improved SE and	Complexity grows with user count
[61]	OTFS-NOMA	Sum-rate maximization	Jonker–Volgenant matching, water-filling	Dynamic joint subcarrier and power allocation adapting to Doppler and mobility	Superior sum rate and SE vs OFDMA, especially in high-mobility scenarios	Increased algorithmic complexity
[62]	Downlink MIMO-NOMA	Network sum-rate maximization with QoS	Water-filling-based cross-cluster PA, closed-form expressions	Cross-cluster dynamic power allocation, weak users are prioritized	Nearly 50% reduction in weak-user outage, improved fairness with high sum rate.	Requires accurate channel gain Information

3.3. Heuristic-Based Optimization

In heuristic-based DPA, power coefficients are dynamically adapted using population-based search methods to optimize system performance under varying network conditions. Heuristic-based dynamic power allocation is needed to handle the non-convexity, high dimensionality, and rapidly time-varying interference of practical NOMA systems, where convex formulations become intractable or computationally prohibitive. The three major classifications of heuristic-based DPA methods are discussed below.

Genetic Algorithms (GA), inspired by principles of natural selection, efficiently explore large solution spaces and adapt power allocation based on channel conditions, user distance, and modulation schemes. GA based frameworks in [63] and [64] jointly optimize user grouping and power allocation for downlink NOMA-OFDM, aiming to maximize geometric-mean throughput. The proposed method achieves near-exhaustive-search performance and improved fairness with substantially reduced complexity, but under assumptions of perfect SIC and fixed system parameters.

Extending GA to energy-harvesting scenarios, [65] presents a joint time power allocation scheme for hybrid NOMA TDMA wireless powered IoT networks. The scheme attains near-optimal throughput gains over pure NOMA and TDMA while relying on ideal SIC and energy-harvesting models. The GA-based fair power allocation strategy introduced in [66] uses three-user PD NOMA that dynamically adjusts transmit power according to channel and modulation conditions, yielding significant BER and fairness improvements over uniform and water-filling schemes at the expense of increased iterative complexity.

Simulated Annealing (SA) is a metaheuristic technique for resource allocation in energy-efficient downlink NOMA systems that offers near-optimal solutions with lower computational complexity and faster convergence than conventional numerical methods. In [67], a SA based scheme jointly optimizes user pairing and power allocation for downlink NOMA to maximize throughput, achieving fast convergence and notable gains with reduced complexity. However, its applicability is constrained to two user pairings and is sensitive to parameter tuning.

Broadening SA to scheduling problems, [68] 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. Authors in [69] presents GA-SA hybrid optimization framework for downlink NOMA-MIMO, that jointly optimizes user pairing and power allocation. SINR and throughput are enhanced with increased fairness and spectral efficiency, but at the expense of higher computational complexity and increased sensitivity to algorithmic parameters.

The Modified Artificial Bee Colony (MABC) algorithm has emerged as an effective metaheuristic for power allocation in NOMA, providing enhanced exploitation capability and improved sum-throughput when compared with conventional evolutionary schemes. In [70], MABC based downlink NOMA power allocation framework is proposed that incorporates global best guidance to optimize power coefficients under total power and minimum rate constraints. The proposed scheme achieves faster convergence and higher throughput than OMA. However, its dependence on parameter tuning and fixed two-user pairing limits scalability in dynamic scenarios. Extending swarm-intelligence approaches to multi-cell systems, [71] introduces a hybrid GA–ABC framework for large-scale NOMA that employs GA for UE–BS association and subchannel assignment. It also proposed an enhanced ABC algorithm for continuous power optimization under QoE constraints, attaining superior QoE and convergence performance compared to OMA and static NOMA. Nevertheless, these achievements are accompanied by increased computational overhead and sensitivity to heuristic parameters in dense network deployments.

Convex optimization methods achieve a global optimal solution, but their practical applicability is limited by their dependence on perfect instantaneous CSI and their iteration complexity, making them infeasible for dense networks. MMF optimization provides strong fairness guarantees but prioritizes edge users at the expense of aggregate throughput. This inherent trade-off demands careful tuning based on operator policy. Heuristic methods overcome the convexity constraint at the expense of optimality guarantees. They exhibit sensitivity to algorithmic-specific parameters like population size and cooling schedules, making deployment calibration non-trivial. A comparative summary of the Heuristic-Based DPA is discussed in Table 5.

4. Artificial Intelligence and Machine Learning (AI/ML) Driven Solutions

The introduction of AI and ML for dynamic power allocation marks a significant shift from model-driven optimization to data-driven learning, motivated by the complexity and non-stationarity of modern wireless channels. These learning-based approaches achieve near-optimal performance with significantly reduced computational overhead while adapting effectively to dynamic channel and traffic conditions in NOMA systems.

Among these approaches, Deep Reinforcement Learning (DRL) has emerged as a promising technique that formulates power allocation as a sequential decision-making process, enabling online policy learning from network states such as CSI, interference, and SIC ordering without relying on exact channel models. Recent advances in hybrid and multi-agent architectures, including Deep Deterministic

Policy Gradient (DDPG), actor critic, prioritized duelling, and Double Deep Q-network (DDQN), further enhance scalability, robustness, and adaptability in large-scale and highly wireless networks. Overall, AI and ML-driven frameworks bridge the gap between static low complexity schemes and dynamic optimization methods, enabling practical, real-time, and intelligent NOMA power allocation for next-generation wireless systems. The following section presents a detailed review of major AI and ML-based power allocation techniques in NOMA networks.

Deep Reinforcement Learning integrates deep neural networks with reinforcement learning to enable decision-making from high-dimensional observations. It is well-suited for dynamic power allocation in NOMA, where the base station learns adaptive policies through interaction with the wireless environment to optimize throughput and QoS. In [73], a DRL-based framework for multi-carrier NOMA employs single-agent DDPG for subcarrier assignment and multi-agent DDPG for power allocation. By integrating constraint-aware learning with CNN/ResNet state representations, the proposed scheme achieves higher throughput and robustness under imperfect SIC and heterogeneous QoS. However, it is associated with high training complexity, long convergence, and reliance on centralized training. Cache-aided downlink NOMA is investigated in [74], where closed-form divide-and-conquer optimization and a DRL-based dual Deep Neural Network (DNN) approach exploit cached content for interference cancellation. User success probability is improved without cooperation, though the DRL solution incurs high training overhead and limited generalization.

Table 5. Heuristic-Based DPA Optimization Techniques in NOMA

Ref.	Technique	System Model	Objective	Methodology	Advantages	Limitations
[63]	GA	Downlink NOMA-OFDM	Fair throughput maximization	Joint user grouping and power allocation	Near-optimal performance, fairness-aware	Assumes perfect SIC
[64]	GA	Downlink NOMA-OFDM	Fair throughput maximization	Large search-space exploration via GA	Fast convergence, fairness gains	Limited real-world adaptability
[65]	GA	Wireless-powered IoT (Hybrid NOMA–TDMA)	Throughput maximization	Joint time–power optimization	Near-optimal throughput, low complexity	Ideal EH and perfect SIC assumptions
[66]	GA	PD-NOMA	Fair power allocation and BER	Dynamic GA-based power adaptation	Significant BER reduction, robustness	High iteration cost
[67]	SA	Downlink NOMA	Throughput maximization	Joint user pairing and power allocation	Fast convergence, low complexity	Parameter sensitivity, 2-user pairing
[68]	Collaborative SA	Uplink NOMA	Make span minimization	Serial SA for clustering and scheduling	Scalable, effective NP-hard handling	Restrictive assumptions
[69]	Hybrid GA–SA	Downlink NOMA-MIMO	SINR / throughput maximization	GA for pairing, SA for power refinement	High SINR, fairness, SE gains	High complexity, parameter tuning
[70]	Modified ABC (MABC)	Downlink NOMA	Throughput maximization	Global-best–guided ABC	Faster convergence than ABC/FTPA	Fixed pairing, scalability limits
[71]	Hybrid GA–ABC	Multi-cell NOMA	QoE (MOS-based) maximization	GA for association, ABC for power	High QoE, mixed-integer efficiency	High heuristic overhead
[72]	GA	Downlink NOMA-OFDM	Throughput and fairness	GA inspired by TSP for joint optimization	Reduced complexity vs exhaustive search	Fixed system assumptions

A NOMA-assisted multi-task Mobile Edge Computing (MEC) framework in [75] employs distributed optimization and a DRL-based online scheme to jointly optimize task offloading, transmission duration, and computation resources. The proposed method achieves notable energy efficiency gains over FDMA. However, scalability and practical deployment in large-scale IIoT deployments are limited by high iterative complexity, DRL training sensitivity, and simplifying assumptions. In [76], a DRL-based uplink grant-free NOMA framework models uncoordinated access as a Partially Observable Markov Decision (POMDP) Process, where it employs a DDQN enhanced with LSTM and a duelling architecture to maximize long-term throughput under collisions. The major drawback is high training complexity and hyperparameter sensitivity in dense networks.

A DDPG-based approach that jointly optimizes BS beamforming and STAR-RIS coefficients for energy-efficient STAR-RIS-assisted NOMA-MISO downlink systems is discussed in [77]. Its reliance on full CSI and costly training constrains its practical application. Authors in [78] proposed a QoS-driven DDQN to optimize UAV trajectories in uplink NOMA-based WPCNs under mobility and energy constraints, achieving significant throughput gains over conventional techniques and heuristic trajectory planning methods.

A DDQN-based downlink NOMA power allocation scheme in [79] incorporates SINR-aware rewards design with channel-based user grouping. In this proposed method, weak user QoS parameters are prioritized, resulting in rapid convergence, improved fairness, and higher SINR than conventional NOMA and Q-learning. However, the framework suffers from reduced sum rate and increased training complexity.

Authors in [80] proposed a multi-agent DQN/DDQN framework that enables open-loop power control for uplink grant-free NOMA using a layer-based power pool without CSI exchange. Simulation results show stable learning, reduced collisions, and higher throughput than GF-OMA and fixed-power schemes, but suffers with high training complexity and limited adaptability in highly dynamic settings. DRL-based DQN and DDQN methods in [81] address the nonconvex joint beamforming and power control problem in single-cell multiuser MIMO NOMA under rate constraints. The system exhibits convergence and significant sum-rate improvement in high-dimensional optimization scenarios.

The multi-agent DDPG framework in [82] jointly optimizes sub band selection and transmit power for NOMA-enabled V2X under latency and reliability constraints. The optimization technique increased V2I throughput and robust V2V performance in high-mobility scenarios. High computational complexity and training instability were the main disadvantages of the system. A DDPG-driven RL scheme that optimizes IRS phase shifts for downlink NOMA under unknown CSI and imperfect SIC was discussed in [83], learning near-optimal unit modulus configurations with performance close to exhaustive search. High training overhead and slow convergence at low SNR were the major drawbacks of the system. In [84], a DDPG-assisted opportunistic NOMA framework jointly optimizes time sharing and transmit power in energy harvesting IoT networks, delivering fast convergence and superior SE/EE under dynamic channel conditions. However, its practical deployment is challenged by scalability challenges due to full-CSI dependence and hyperparameter sensitivity.

A hybrid optimization DRL framework is presented in [85] that jointly addresses D2D-NOMA cluster association and power allocation by combining weighted bipartite matching and a Dinkelbach-enhanced TD3 algorithm. It achieves near exhaustive search energy efficiency and outperforms DDPG and DQN-based schemes at the expense of high training complexity and hyperparameter sensitivity. In [86], a DDPG-based DRL framework is proposed for uplink NOMA-enabled cognitive radio networks with energy harvesting secondary users, demonstrating improved long-term throughput compared to DQN and actor critic methods while enabling concurrent spectrum access and sharing.

In [87], a deep actor critic RL framework models dynamic power and bandwidth allocation in hybrid NOMA/OMA uplink cognitive radio networks as a Markov Decision Process (MDP). Higher long-term throughput and energy efficiency are achieved without prior channel or energy statistics, but at the cost of high training complexity and ideal SIC assumptions. The authors in [88] proposed a Soft Actor Critic(SAC) based approach that jointly optimizes BS transmit power and reflection coefficients for uplink backscatter NOMA. Results proved delivering improved adaptability and SE/EE gains in dynamic environments while relying on ideal CSI/SIC and incurring significant training overhead.

A two-phase framework in [89] combines actor-critic RL for source power control with Sequential Convex Approximation (SCA) at the relay in EH-enabled mm Wave NOMA networks, providing improved sum rate and energy efficiency under uncertainty. High computational complexity and deployment challenges on energy-constrained nodes were the challenges faced by the system. In [90], an actor-critic RL framework is employed to realize adaptive power allocation for downlink power domain NOMA under a sum power constraint, achieving significant energy efficiency gains over conventional schemes through channel-aware policy learning.

A hybrid framework in [91] combines closed-form water filling power allocation with an actor critic based DRL agent for user pairing in downlink multi-carrier NOMA. Higher sum rates and faster convergence than DQN and OMA were delivered at the cost of perfect CSI reliance and limited scalability in user pairing decisions. In [92], a hybrid Prioritized Dueling DQN DDPG architecture is presented that jointly optimizes discrete user grouping and continuous power allocation for uplink NOMA, providing superior sum rate performance and faster, more stable convergence than conventional DQN DDPG at the cost of higher computational complexity and CSI dependence. A prioritized DQN–DDPG scheme for uplink NOMA in IoV was discussed in [93], which accelerates user grouping via Temporal Difference (TD) error-based sampling and enables quantization-free power control, delivering near exhaustive search performance. But it was associated with additional training overhead and reliance on ideal CSI/SIC assumptions.

A DNN-based resource management framework for downlink NOMA in [94] jointly performs power allocation and user scheduling by approximating interior point method solutions. Limited adaptability to fast channel variations made it less suitable for dynamic NOMA environments. In [95], a DNN-driven user clustering and power allocation scheme captures nonlinear channel power mappings to deliver near-theoretical throughput with reduced complexity. However, extensive training data requirements and careful hyperparameter tuning added the cost overhead of the system.

4.1. Fuzzy Logic and Other AI-Based Heuristics

A fuzzy logic-based coordinated multi cell NOMA framework is proposed in [96], that optimized user mode selection and resource allocation to improve spectral and energy efficiency under inter-cell interference, at the expense of added signalling overhead and parameter sensitivity. An adaptive fuzzy logic power allocation scheme in [97] tackles cooperative NOMA with imperfect SIC by learning power coefficients from user SNR and channel variations. It achieved near-optimal outage and fairness with low computational complexity. In [98], a fuzzy inference system-based power allocation approach for downlink PD-NOMA, incorporating user distance, SNR, and foliage depth, is introduced. It significantly improves edge BER and fairness in mm Wave micro cells, particularly when combined with cooperative decode and forward relaying.

The authors in [99] introduced an AI-driven framework for RIS-assisted NOMA in IoT that jointly optimizes transmit power and RIS phase shifts by integrating alternating optimization, KKT-based refinement, and Exploration Attenuated (EA) DDPG learning, achieving significant gains in sum rate, energy efficiency, and adaptability over conventional schemes for future 6G IoT networks. In [100], AI-assisted power allocation models for downlink single cell NOMA employ regression and DNN predictors trained on user BS distances to approximate an exhaustive-search solution. It provided, achieving near-optimal sum capacity with orders-of-magnitude lower complexity, under assumptions of perfect SIC, single-cell operation, and offline training using optimal labels.

DRL-based methods have emerged as the most promising paradigm for 6G-scale NOMA, but significant deployment barriers remain. Training convergence for DDPG in continuous, high-dimensional action spaces can require extensive training, which is impractical for online learning without a simulation infrastructure. Furthermore, the majority of published DRL-PA works assume centralized training with full CSI access, and with that assumption, which is often inconsistent with the decentralized, privacy-sensitive architecture of 6G edge networks. The gap between offline training performance and online generalization under distribution shift, such as changes in new user densities and channel models, remains largely unquantified in the literature. Table 6 will give a brief comparative study of various AI/ML and fuzzy-based power allocation strategies in NOMA. Table 7 compares specific AI/ML architectures employed for NOMA power allocation.

Table 6. AI/ML and fuzzy-based optimization techniques in NOMA

Ref.	Scenario	Method	Objective	Highlighted Strengths	Key Limitations
[73]	Downlink NOMA	DRL	System throughput maximization	Robustness under imperfect CSI	High training complexity
[74]	Downlink NOMA	DRL	SE optimization	Stable learning handles continuous states and actions.	Convergence depends on critic accuracy.
[75]	NOMA–MEC (IIoT)	DRL	Energy efficiency	Near-optimal EE, fast online decisions	Iterative overhead, limited scalability

[76]	Grant-free uplink NOMA	DRL+ LSTM	Long-term throughput	Collision mitigation, scalable under heavy load	Large state/action space, training complexity
[77]	STAR-RIS NOMA–MISO	DDPG	EE maximization	Joint beamforming and RIS control	Full CSI, no global optimality
[78]	UAV–NOMA WPCN	Double DQN	Throughput	QoS-aware trajectory learning	UAV energy and training overhead
[79]	Downlink NOMA	DDQN	QoS-aware PA	Fast convergence, fairness for weak users	Reduced sum rate, tuning sensitivity
[80]	Grant-free uplink NOMA	Multi-agent DQN/DDQN	Throughput	Open-loop PA, stable SIC gaps	Replay buffer and training overhead
[81]	MIMO–NOMA	DQN / DDQN	Sum-rate	Handles high-dimensional joint PA/beamforming	Large training complexity
[82]	V2X NOMA	Multi-agent DDPG	V2I throughput	Continuous joint PA and spectrum selection	Training instability
[83]	IRS–NOMA	DPPG	Sum-rate	Near-optimal IRS phase control under unknown CSI	Slow convergence at low SNR, DRL overhead
[84]	Energy Harvest IoT NOMA	DDPG + convex	SE / EE	Adapts to EH dynamics	Full CSI requirement
[85]	D2D–NOMA HetNet	TD3 + Dinkelbach	Long-term EE	Near-exhaustive performance	High DRL complexity
[86]	NOMA with CR	DDPG	Throughput maximization	Secondary Users have better performance	Computational complexity
[87]	Uplink CR NOMA	Deep Actor–Critic RL	System throughput maximization	Continuous PA, adaptive to channel dynamics	High training cost, hyperparameter sensitivity, and ideal SIC assumptions
[88]	Backscatter NOMA	SAC	Uplink sum-rate	Robust to interference and noise	High training cost
[89]	EH relay NOMA	Actor–Critic + SCA	Sum-rate / energy	EH-aware adaptation	Computationally intensive
[90]	Downlink NOMA	Actor–Critic	EE	Stable adaptive PA	Limited scalability analysis
[91]	MC-NOMA	Actor Critic + water-filling	Sum-rate	Closed-form PA, fast convergence	Perfect CSI, pairing limits
[92]	Uplink NOMA	Prioritized Dueling DQN + DDPG	Sum-rate	Stable, fast learning	High complexity
[93]	IoV uplink NOMA	Prioritized DQN + DDPG	Throughput	Near-exhaustive performance	Ideal CSI/SIC
[94]	Downlink NOMA	DNN	Sum-rate	Near-IPM performance, low inference cost	Limited adaptability
[95]	Downlink NOMA	DNN	Clustering + PA	Near-optimal with low complexity	Large training data
[96]-[98]	Multi-cell / Coop. NOMA	Fuzzy logic	EE/fairness	Robust, low real-time complexity	Rule/parameter tuning
[99]	RIS–NOMA IoT	EDDL and EA-DDPG	EE / sum-rate	Highly adaptive, 6G-ready	Heavy training cost
[100]	Downlink NOMA	Regression and DNN	Sum-capacity	Orders of magnitude complexity reduction	Needs optimal labels

Table 7. Comparison of AI/ML architectures employed for NOMA power allocation

ML Method	Architecture	Training Mode	CSI Tolerance	Scalability	Best Use Case
DQN/DDQN	Deep Q-Network	Offline/Online	Moderate	Medium	User grouping, discrete PA
DDPG	Actor-Critic	Offline	Moderate	Medium	Continuous PA optimization
TD3	Twin Delayed DDPG	Offline	High	Medium-High	High-variance PA environments
SAC	Stochastic Actor-Critic	Offline	High	High	Entropy-regularized PA
MADDPG	Multi-Agent DDPG	Offline (centralized)	Moderate	High	Multi-cell/D2D NOMA
DNN Surrogate	Supervised MLP	Offline (batch)	Low	Very High	Near-instant inference; stable channels
Fuzzy Logic	Rule-based FIS	No training	High	Medium	Low-complexity adaptive PA

Table 8. Comparative study of SA, DPA, and AI/ML based power allocation in NOMA

Parameter	Static Power Allocation	Dynamic Power Allocation	AI / ML-Based Power Allocation
Adaptability to Channel Variations	None; depends on fixed rules or long-term statistics	High, dynamically adapts to instantaneous CSI and interference conditions	Very high, learns and adapts to dynamic operating conditions in real time
Computational Complexity	Very low	High due to iterative optimization	Moderate online (high offline training cost)
Requirement of CSI	Long-term or average CSI	Accurate instantaneous CSI required	Can operate with partial, noisy, or delayed CSI
Spectral Efficiency	Low to moderate	High	Near-optimal / high
User Fairness	Limited and scenario-dependent	Explicitly controllable via constraints	Learned implicitly or explicitly through reward function design
SIC Reliability	May degrade under dynamic conditions	Ensures strong SIC feasibility through power separation constraints	Learns SIC-aware policies, robust to imperfections
Interference Management	Fixed and inflexible	Explicitly optimized	Learned and adaptive across time and users
QoS Guarantee	Weak for heterogeneous users	Strong via optimization constraints	Strong via reward shaping or supervised targets
Scalability (Users / Clusters)	Poor in dense networks	Limited due to the complexity growth	High, scalable with proper model design
Real-Time Suitability	High	Limited	High after training
Robustness to Imperfect CSI	Low	Low to moderate	High
Implementation Complexity	Simple	Complex	Moderate (training and deployment)
Optimization Nature	Rule-based, non-iterative	Nonconvex, NP-hard optimization	Data-driven, model-free, or hybrid
Typical Techniques	FPA, GRPA, distance-based	Convex approximation, dual decomposition, AO	RL, DRL, supervised learning, surrogate models
Best Use Case	Low-mobility, simple systems	Performance-critical but manageable-scale systems	Large-scale, dynamic, interference-limited networks

Table 9. Identified research gaps with their priority for future investigation

Research Gap	Current State	Future Direction	Relevance to 6G
Imperfect SIC in AI models	Most DRL models assume perfect SIC	SIC-error-aware reward functions in DRL	Critical – 6G dense networks amplify SIC imperfections
Federated / distributed learning	Mostly centralized DRL training	Federated RL for privacy-preserving PA	Essential – 6G edge intelligence mandates decentralized learning
NOMA + RIS integration	Early-stage; limited joint optimization	End-to-end DRL for joint RIS+NOMA PA	High – RIS is a key 6G enabler
NOMA + Terahertz (THz) channels	Nascent; few channel-aware PA studies	PA strategies accounting for THz blockage and absorption	High – THz bands targeted for 6G
Explainability of AI-PA	Black-box DRL decisions	Interpretable ML for PA accountability	Moderate – needed for standardization
Cross-layer integration	Physical-layer-only optimization	Joint MAC + PHY DRL for NOMA PA	High – 6G requires a holistic design
Energy harvesting + PA	Simplified EH models	Realistic EH-aware DRL with non-linear models	High – 6G green communication mandate
Benchmarking standards	Inconsistent simulation setups across papers	Unified open-source NOMA PA benchmark suite	Moderate – needed for reproducible research

5. Results and Discussions

Having reviewed static, optimization-based dynamic, and AI/ML-driven power allocation strategies for NOMA systems, it is shown that each category is developed under distinct design techniques, complexity constraints, and performance objectives. While static schemes emphasize simplicity and low signaling overhead, dynamic optimization approaches prioritize instantaneous CSI exploitation and performance maximization. AI/ML-based methods, on the other hand, aim to introduce adaptability and learning capability in highly complex and interference-dominated environments. To better understand their relative strengths, limitations, and suitability for 5G and emerging 6G scenarios, a structured comparative analysis is now presented in Table 8. Table 9 consolidates identified research gaps with their priority for future investigation.

6. Conclusion

This survey has systematically reviewed and analysed power allocation schemes encompassing the entire spectrum of NOMA power allocation paradigms from fixed-coefficient static schemes to AI/ML-driven adaptive frameworks. The analysis demonstrates a clear evolutionary trajectory in the development of the NOMA power allocation strategy. Static methods established the foundational principles and identified the core trade-offs between implementation complexity and system performance. Dynamic optimization methods exploited instantaneous CSI to approach theoretical performance limits.AI/ML methods are now redefining the frontier by enabling adaptive, scalable, and robust PA in conditions where classical methods are fundamentally inadequate.

The progression from static to dynamic and AI-enabled power allocation reflects the increasing demand for adaptability, intelligence, and spectrum efficiency in 5G and beyond 5G networks. Power allocation frameworks in the future must integrate optimization theory, stochastic interference modelling, and learning-based adaptability to accommodate dense deployments, heterogeneous QoS requirements, and stringent reliability constraints. Developing hybrid model-driven and data-driven approaches is expected to play a major role in realizing energy-efficient, scalable, and autonomous NOMA-enabled next-generation wireless systems.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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