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REVIEW ARTICLE

INTERFERENCE MITIGATION IN B5G NETWORKS: A CRITICAL REVIEW OF CONVENTIONAL, OPTIMIZATION-BASED, AND AI-DRIVEN TECHNIQUES

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ABSTRACT

Beyond fifth generation (B5G) networks require effective interference mitigation to maintain high throughput, low latency, spectral efficiency, and reliable communication in dense and dynamic environments. This paper presented a structured critical review of B5G interference-mitigation techniques. Twenty-five studies were selected from major scientific databases based on clearly defined interference problems, mitigation methods, implementation approaches, and measurable performance outcomes. The techniques were grouped into conventional and coordination-based, optimization-based, and artificial-intelligence-driven approaches. Conventional methods such as power control, fractional frequency reuse, coordinated scheduling, coordinated multipoint transmission, and beamforming remain effective but may lack adaptability under rapidly changing conditions. Optimization-based methods provide systematic resource control but are limited by computational complexity and dependence on network-state information. AI-driven approaches, particularly reinforcement and deep reinforcement learning, offer greater adaptability but face challenges involving training, convergence, computational demand, and signaling overhead. Overall, no single technique is universally suitable; effective B5G interference management requires balancing performance gains with complexity, scalability, overhead, and practical implementation.

1.0 Introduction

Beyond fifth generation (B5G) networks are being developed to support high data rates, low latency, reliable communication, wide coverage and efficient spectrum utilization (Imam-Fulani *et al.*; 2023). Technologies such as ultra-dense deployment, massive multiple-input multiple-output, millimetre-wave communication and intelligent radio-resource control are expected to support these requirements (Trabelsi *et al.* 2024). However, their performance depends strongly on effective interference management.

Interference occurs when unwanted signal interactions degrade communication quality. In dense B5G environments, simultaneous transmissions within the same or adjacent frequency bands can reduce signal-to-interference-plus-noise ratio and throughput while increasing delay and outage probability, thereby affecting energy efficiency and service reliability (Alzubaidi *et al.* 2025). These effects become more challenging under rapidly changing traffic, mobility and channel conditions.

Conventional interference-mitigation techniques include power control, fractional frequency reuse, inter-cell interference coordination, coordinated multipoint transmission, beamforming and interference-aware scheduling (Siddiqui *et al.* 2021). Although these techniques remain relevant, their performance can be constrained by coordination requirements and dependence on channel information in highly dynamic environments (Mahmud and Hamdi; 2014; Khan *et al.* 2019). Optimization-based methods address these limitations by adjusting variables such as transmission power, channel allocation, user association, scheduling and beam selection to improve spectral efficiency, energy efficiency, throughput and fairness (Naqvi *et al.* 2018; Hasan *et al.* 2023). However, their computational requirements and dependence on accurate network-state information may limit real-time application in large B5G networks (Mismar *et al.* 2019).

Artificial-intelligence-driven approaches provide greater adaptability by learning from network conditions and supporting interference-aware power control, channel selection, scheduling and resource allocation (Lohan *et al.* 2024; Mismar *et al.* 2019). Nevertheless, their effectiveness may be affected by training requirements, computational cost, convergence, explainability and generalization to changing network conditions (Tan *et al.* 2020).

Although previous reviews have examined interference management in 5G and beyond networks, reported techniques are often evaluated under different network scenarios, assumptions, simulation settings and performance metrics, making direct comparison difficult (Alzubaidi *et al.* 2025). A focused synthesis is therefore needed in which individual mitigation studies are examined according to the technique employed, interference condition addressed, implementation method, reported performance and identified limitations.

This paper critically reviews interference-mitigation techniques relevant to B5G networks, with emphasis on conventional and coordination-based, optimization-based and artificial-intelligence-driven approaches.

2. Method

This study adopted a structured literature-review approach to examine interference-mitigation techniques in B5G and closely related 5G-Advanced networks. Studies were included only when they proposed, applied, evaluated or compared a specific mitigation technique. Network settings such as device-to-device communication, heterogeneous networks, ultra-dense networks and dynamic TDD were considered only as environments in which interference-mitigation techniques were evaluated.

Relevant studies were identified from IEEE Xplore, Scopus, Web of Science, ScienceDirect, SpringerLink and Google Scholar. The search covered publications from 2014 onward, with greater emphasis on studies published from 2020 onward. Search terms included combinations of “B5G interference management,” “interference mitigation,” “power control,” “interference-aware resource allocation,” “beamforming,” “coordinated interference mitigation,” “optimization-based interference management,” “machine-learning interference mitigation,” “deep-learning interference management,” “reinforcement-learning interference management” and “hybrid interference-management schemes.”

Studies were included if they addressed a clearly defined interference problem, investigated a specific mitigation technique, described its implementation or evaluation method, and reported measurable outcomes such as SINR, throughput, spectral or energy efficiency, outage probability, latency, fairness or convergence. The selection process followed four stages, as illustrated in Figure 1.

The selected studies were analyzed using a thematic synthesis approach. Information was extracted based on interference type, network scenario, mitigation technique, performance metric, strength, limitation, and deployment relevance. This allowed the reviewed studies to be grouped under major themes, including interference sources, conventional methods, optimization-based techniques, AI-driven approaches, standards-based mechanisms, and open research challenges.

3. Discussion of Results

Interference management in B5G networks is increasingly challenging because of dense spectrum reuse, heterogeneous deployments, D2D communication, dynamic TDD operation and emerging terrestrial–non-terrestrial coexistence. Rather than treating these interference conditions separately, Table 1 linked each scenario directly to the mitigation techniques reported in the literature. D2D and heterogeneous deployments may generate co-tier and cross-tier interference, requiring interference-aware channel allocation, power control and resource coordination (Tan *et al.* 2021; Hasan *et al.* 2023). Inter-cell and dynamic-TDD interference particularly affected neighbouring cells and cell-edge users, motivating techniques such as fractional frequency reuse, coordinated scheduling and cross-link interference coordination (Mahmud and Hamdi, 2014; Kim *et al.* 2020; Pedersen *et al.* 2021). Where terrestrial and non-terrestrial systems share spectrum, coordinated resource and beam management may also be required (Ding *et al.* 2024). These scenarios provided the context for the interference-mitigation techniques reviewed in the following sections.

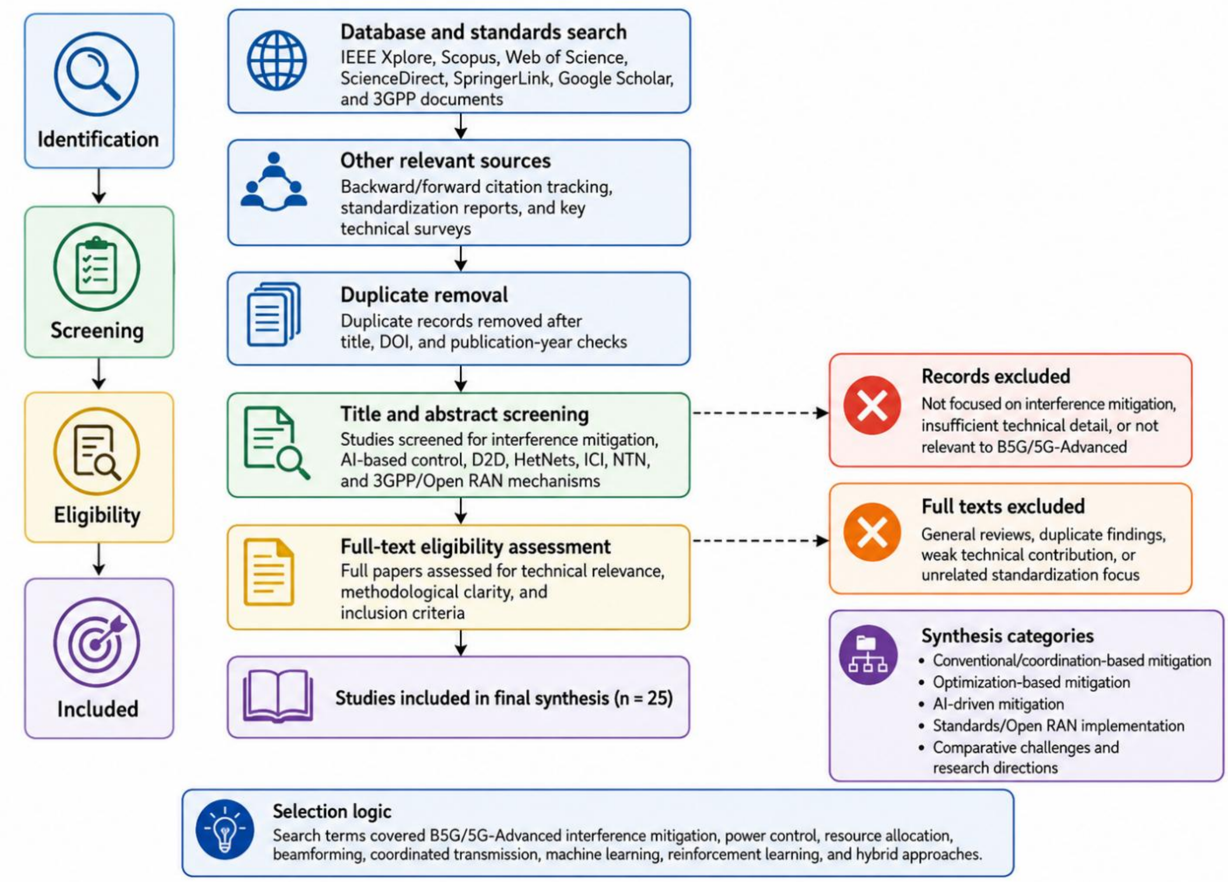

Figure 1: Literature screening and selection flow for the structured review

3.1 Review of Interference-Management Techniques

To provide context for the interference-mitigation techniques reviewed in this study, Table 1 summarizes representative interference scenarios encountered in B5G and closely related network environments, together with their principal causes, performance effects, and corresponding mitigation approaches reported in the literature. The table is not intended to treat interference sources as a separate review theme; rather, it established a direct link between each interference condition and the techniques employed to mitigate it. This provided the basis for the subsequent discussion of conventional and coordination-based, optimization-based, AI-driven, and standards-aligned interference-management approaches.

Interference management in B5G networks involves the control of radio resources, transmission power, spatial transmission and coordination among network entities to limit unwanted interference while maintaining spectral efficiency and quality of service. Recent literature had investigated frequency-reuse schemes, coordinated transmission, power control, beamforming, dynamic-TDD coordination and learning-based resource management as important approaches for interference mitigation in dense and heterogeneous wireless networks. (Trabelsi *et al.* 2024) provided a comprehensive classification of these approaches and emphasized that the appropriate mitigation method depended on the interference characteristics, network architecture and available coordination information.

Khan *et al.* (2019) proposed a fractional frequency reuse scheme termed FFR-3SL for mitigating co-channel interference in heterogeneous cellular networks. The scheme divided available radio resources across three sectors and three layers to improve frequency reuse while limiting interference between neighbouring transmission regions. Their simulations showed that FFR-3SL provided higher throughput and system capacity than the comparative frequency-reuse schemes considered in the study. Although the work was developed for LTE-A HetNets, the resource-partitioning principle provided a conventional interference-management baseline for increasingly dense heterogeneous deployments.

Dynamic TDD requires specific coordination because neighbouring cells may simultaneously schedule transmissions in opposite directions. (Kim *et al.* 2020) examined cross-link interference mitigation in dynamic-TDD systems for 5G and beyond and reviewed techniques for controlling the resulting base-station-to-base-station and user-to-user interference. The study showed that effective dynamic-TDD operation requires interference-aware coordination rather than independent adjustment of uplink and downlink traffic by individual cells. Pedersen *et al.* (2021) subsequently examined 5G New Radio mechanisms for mitigating co-channel cross-link interference between neighbouring cells and also considered remote interference occurring between geographically separated cells. Their analysis demonstrated the importance of coordinated TDD operation when traffic-direction flexibility was used in dense deployments.

Table 1: Interference Scenarios Addressed by Representative Interference-Mitigation Techniques

Interference source	Main cause	Main impact	Typical mitigation methods	reference(s)
D2D interference	Spectrum reuse between D2D and cellular users	Co-channel/cross-tier interference and reduced SINR	Power control, mode selection and resource allocation	(Tan *et al.* 2020), (Naqvi *et al.* 2018)
HetNet interference	Coexistence of macro-, pico-, femto- and small-cell tiers using overlapping spectrum	Co-tier/cross-tier interference, load imbalance and degradation of cell-edge performance	FFR, eICIC, coordinated resource allocation and interference-aware radio-resource management	(Khan *et al.* 2019); (Naqvi *et al.* 2018); (Hasan *et al.* 2023)
Inter-cell interference	Reuse of the same or adjacent frequency resources by neighbouring cells	Reduced SINR, throughput and QoS, particularly for cell-edge users	FFR, beamforming and coordinated scheduling	(Mahmud & Hamdi 2014), (Khan *et al.* 2019)
Dynamic TDD cross-link interference	Different UL/DL transmission directions in neighbouring cells using the same time-frequency resources	BS-to-BS and UE-to-UE cross-link interference, resulting in SINR and throughput degradation	UL/DL coordination, interference-aware scheduling, clustering and interference cancellation	(Kim *et al.* 2020); (Pedersen *et al.* 2021)
Terrestrial–NTN interference	Spectrum sharing and overlapping coverage between terrestrial base stations and non-terrestrial satellite links	Co-frequency interference, reduced SINR/throughput and increased outage probability	Beam scheduling, power control, interference-aware resource allocation and coordinated spectrum sharing	(Ding *et al.* 2024)

Resource allocation and power control had also been investigated for D2D interference mitigation. Tan *et al.* (2020) formulated joint channel selection and power control in an overlay D2D network as a weighted-sum-rate maximization problem. They first applied fractional programming to obtain a near-optimal solution but identified the requirement for instantaneous global channel-state information and centralized computation as scalability constraints. They therefore developed a distributed deep-reinforcement-learning scheme in which individual D2D pairs selected channels and transmission power using local and outdated non-local information, thereby reducing dependence on centralized information exchange.

Mismar *et al.* (2019) investigated the joint application of beamforming, power control and interference coordination in 5G networks. The problem was formulated as a non-convex optimization task and employed deep reinforcement learning to select suitable transmission decisions. The simulations demonstrated improvements in SINR and sum-rate performance; for the investigated millimetre-wave data-bearer scenario, the learning-based solution approached the maximum sum-rate benchmark while requiring substantially less computation time. This study illustrated how learning can combine several interference-control variables rather than optimizing beamforming or transmit power independently.

More recent studies had focused on reducing the communication overhead associated with distributed learning. (Dahal and Vaezi, 2025) proposed a multi-agent reinforcement-learning method for inter-cell interference mitigation in which neighbouring base-station agents shared only selected useful experiences rather than exchanging their complete learning histories. The method supported decentralized training and execution. Their results showed that reducing experience sharing by 75% retained approximately 98% of the spectral efficiency achieved when all experiences were shared. This addressed an important limitation of learning-based interference management because excessive information exchange can itself impose substantial signaling overhead in dense networks.

AI-based methods therefore extended conventional interference-management approaches by learning adaptive power, channel, beam and scheduling decisions from changing network conditions. However, (Lohan *et al.* 2024) found that the practical application of AI/ML to interference detection and mitigation still depended on appropriate training data, computational requirements, model robustness and the ability of the learning system to respond to changing interference conditions. Consequently, learning-based methods are better viewed as complementary mechanisms that can enhance conventional resource allocation, power control and spatial coordination rather than as complete replacements for established interference-control techniques. Figure 2 shows the taxonomy of B5G interference mitigation techniques while Table 2 gives a summary of comparative synthesis of interference-mitigation studies relevant to B5G.

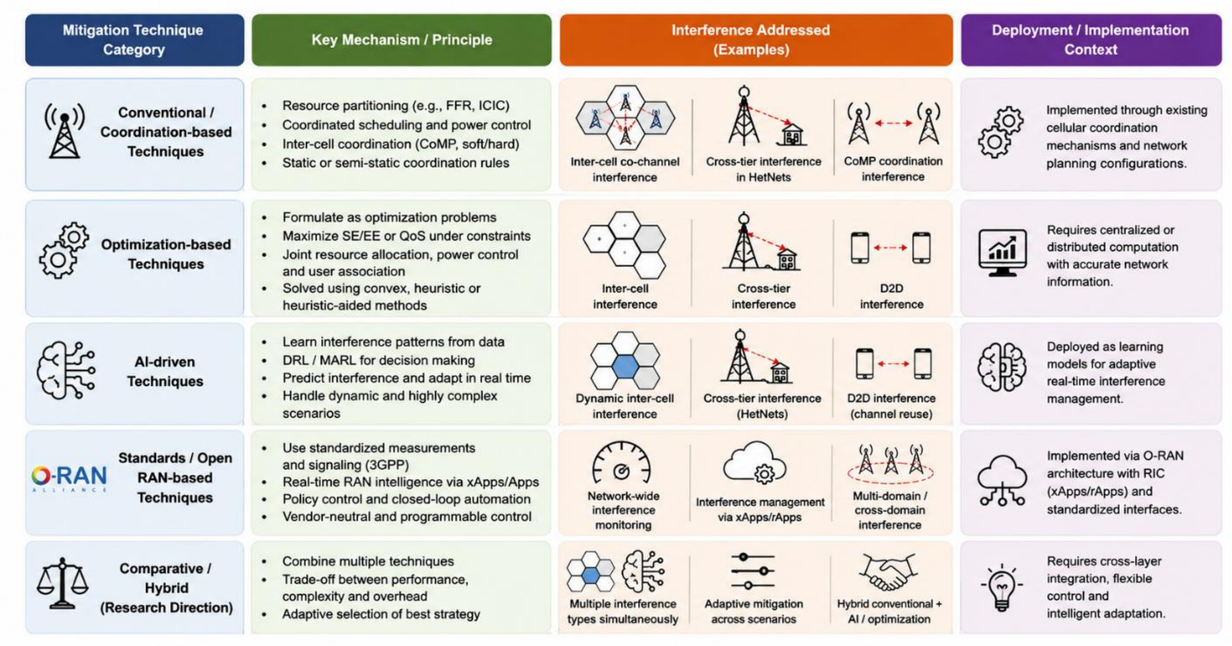

Figure 2: Taxonomy of B5G interference-management techniques and their deployment suitability

Table 2: Comparative synthesis of representative interference-mitigation studies relevant to B5G networks

Approach	Ref.	Mitigation technique	Interference/scenario addressed	Main reported finding	Limitation/relevance to B5G
Conventional	Khan *et al.* (2019)	Fractional frequency reuse (FFR-3SL)	Co-channel interference in heterogeneous cellular networks	The proposed FFR scheme improved radio-resource utilization, throughput and system capacity relative to the comparison schemes evaluated in the study.	Evaluated in an LTE-A HetNet setting; therefore, its direct application to more dynamic B5G environments requires adaptation.
Coordinated/Dynamic TDD	Kim *et al.* (2020)	Cross-link interference coordination and mitigation	BS-to-BS and UE-to-UE interference arising from asynchronous UL/DL transmission	The study systematically classified cross-link interference mechanisms and mitigation approaches for dynamic-TDD operation in 5G and beyond systems.	Effective mitigation requires coordination and interference information, which can increase implementation and signaling requirements.
Optimization/resource allocation	Hasan *et al.* (2023)	Evolutionary biogeography-based dynamic subcarrier allocation	Cross-tier interference in dense 5G HetNets	The proposed resource-allocation scheme produced improved outage and spectral-efficiency performance relative to the comparison techniques evaluated by the authors.	Performance was established through system-level simulation; practical deployment and scalability remain separate considerations.
AI-driven	Mismar *et al.* (2020)	Deep reinforcement learning for joint beamforming, power control and interference coordination	Joint power, beam and inter-cell interference-management problem	The DRL approach jointly selected beamforming, power-control and interference-coordination actions while substantially reducing computational time compared with exhaustive brute-force search in the evaluated scenarios.	Requires training and convergence and its performance depends on the states, actions and network conditions represented during learning.
Comprehensive synthesis	Trabelsi *et al.* (2024)	Classification and comparative review of interference-management schemes	Multiple interference conditions in 5G and beyond networks	The review shows that interference management spans several interference classes and requires mitigation methods adapted to the particular radio-access and network scenario.	As a review study, it synthesizes existing approaches rather than validating one mitigation algorithm experimentally.

3.2 Standards-Based and Open RAN-Aligned Interference Mitigation

Standard-aligned mechanisms provided practical frameworks for implementing interference-control techniques in cellular networks. In 5G New Radio (NR), standardized procedures supported cross-link interference handling, coordinated radio operation and transmission control (Lin, 2025). Standardization should therefore be viewed not as a separate mitigation technique, but as an implementation framework for specific interference-control mechanisms.

Pedersen *et al.* (2021) examined cross-link interference mitigation in 5G NR dynamic-TDD systems, focusing on co-channel interference between neighbouring cells. They investigated UE-assisted interference sensing, coordinated TDD-frame configuration and reinforcement-learning-assisted adaptation. System-level evaluations in macro-cell and indoor-factory scenarios showed that coordinated adaptation can improve dynamic-TDD operation, demonstrating the need for effective interference detection and coordination.

Open RAN provides a programmable environment for implementing adaptive interference-management functions. (Hoffmann *et al.* 2024) examined xApp design and implementation and identified challenges involving network information, software integration, interfaces and low-level control. Their findings indicated that Open RAN was best regarded as an enabling control architecture within which interference-mitigation algorithms can operate rather than as a mitigation technique itself.

More directly, (Anand and Muntean; 2026) developed a machine-learning-driven xApp for interference management in 5G Open RAN heterogeneous networks. Their MLCIMO framework combined multi-binary interference classification with user offloading to mitigate interference and improve quality of service, illustrating how AI-based mitigation can be integrated into the Open RAN control framework.

Overall, standards-based procedures and Open RAN architectures complement interference-mitigation techniques by providing interoperable coordination and programmable implementation environments. Their practical relevance therefore depended on distinguishing the mitigation algorithm from the architecture through which it was deployed.

3.3 Comparative Analysis, Remaining Challenges and Research Directions in B5G Interference Mitigation

The reviewed literature showed that interference-mitigation techniques varied in adaptability, information requirements, computational burden and suitability for dynamic networks. Conventional methods such as power control, fractional frequency reuse, coordinated scheduling and beamforming remained useful because they directly controlled radio resources without extensive learning. However, increasing network heterogeneity and diverse interference conditions demanded more adaptive coordination than static or semi-static techniques can provide. Consequently, mitigation performance depended largely on the interference scenario, available network information and coordination architecture rather than on any universally superior technique (Trabelsi *et al.*, 2024).

Optimization- and learning-based methods offered greater flexibility but introduced training, computational and information requirements. (Mismar *et al.* 2020) applied deep reinforcement learning to jointly optimize beamforming, power control and interference coordination, demonstrating the advantage of jointly controlling multiple variables. Similarly, (Lohan *et al.* 2024) highlighted the adaptability of AI/ML for interference and jamming mitigation while identifying challenges related to implementation and dependable operation.

Signaling and coordination overhead also constrained distributed approaches, particularly when neighbouring entities repeatedly exchanged observations, channel information or learning experiences. (Dahal and Vaezi; 2025) addressed this through selective experience sharing in multi-agent reinforcement learning, showing that a 75% reduction in shared experiences retained approximately 98% of the spectral efficiency achieved with full sharing. Thus, learning-based schemes should be evaluated not only by SINR or throughput gains but also by the communication overhead required to achieve them.

Scalability and practical implementation remained unresolved. (Alzubaidi *et al.* 2025) identified continuing research needs in resource allocation, power control, load balancing, federated learning and cross-domain interference management, emphasizing evaluation under heterogeneous rather than simplified scenarios. Approaches requiring continuous centralized optimization or extensive channel-state information may become difficult to scale as network density and the number of controlled resources increase.

Future research should therefore prioritize lower-complexity, coordination-efficient and deployment-oriented solutions. Lightweight learning is needed for resource-constrained real-time operation, while distributed schemes should minimize information exchange. Explainability, robustness, federated learning and cross-domain interference management also require further investigation in B5G networks (Alzubaidi *et al.* 2025).

Overall, no single mitigation technique was universally preferable. Technique selection depended on the interference scenario, network density, available channel and traffic information, response-time requirements, and acceptable computational and signaling overhead. Conventional methods provided established control mechanisms, optimization approaches enabled systematic resource allocation, and AI-assisted methods offered adaptability. The key research challenge was therefore to achieve measurable interference-mitigation gains while maintaining manageable complexity, scalability, signaling overhead and practical implementation (Trabelsi *et al.*, 2024; Alzubaidi *et al.*, 2025). Table 3 gives some of the challenges and research direction in B5G interference mitigation.

Table 4: Remaining Challenges and Research Directions in B5G Interference Mitigation

Remaining challenge	Evidence from reviewed literature	Research direction	References
Scalability of interference management	Increasing network density, heterogeneity and spectrum reuse increase the number of interacting links and complicate interference coordination.	Develop distributed and scalable interference-management schemes with reduced dependence on centralized coordination.	(Trabelsi *et al.* 2024); (Alzubaidi *et al.* 2025)
Signalling and coordination overhead	Distributed and multi-agent interference-control methods may require repeated exchange of network observations or learning information.	Reduce the amount and frequency of information exchanged while retaining interference-mitigation performance.	(Dahal and Vaezi; 2025)
Computational complexity	Joint optimization of power, beamforming, scheduling and other radio resources can create high-dimensional and non-convex decision problems.	Develop lower-complexity optimization and learning methods suitable for real-time interference control.	(Mismar *et al.* 2020; Trabelsi *et al.* 2024)
Dependence on network information and training data	Optimization methods may require channel/network-state information, while learning approaches depend on representative observations or training data.	Design interference-management approaches that operate reliably with reduced or imperfect network information.	(Trabelsi *et al.* 2024); Alzubaidi *et al.* 2025)
Adaptation to dynamic interference conditions	Static or semi-static methods may become less effective as traffic, user distribution and interference conditions change.	Investigate adaptive resource allocation, power control and learning-assisted interference mitigation capable of responding to changing radio conditions.	(Alzubaidi *et al.* 2025)
Practical implementation and evaluation	Many interference-management schemes are evaluated under specific models or simulation conditions, making comparison and deployment assessment difficult.	Evaluate proposed mitigation methods under realistic heterogeneous scenarios using common performance measures and explicit complexity/overhead assessment.	(Trabelsi *et al.* 2024; Alzubaidi *et al.* 2025)

4. Conclusion

This review examined conventional and coordination-based, optimization-based, AI-driven, and standards-aligned interference-mitigation approaches for B5G networks. As radio-access environments become denser, more heterogeneous and dynamic, conventional techniques such as power control, fractional frequency reuse, coordinated scheduling, ICIC/eICIC, CoMP and beamforming remain important for controlling co-channel, inter-cell and cross-tier interference, although their effectiveness depends on changing traffic, channel and interference conditions.

Optimization-based approaches enable joint control of transmission power, spectrum, scheduling and beamforming but may be constrained by computational complexity and the need for timely network-state information. AI-driven methods, particularly reinforcement and deep reinforcement learning, offer greater adaptability and support joint resource-management decisions, but introduce challenges related to training, convergence, computational demand, signaling overhead and representative network information.

Effective interference mitigation should therefore be evaluated not only by SINR, throughput and spectral-efficiency gains, but also by scalability, computational requirements, coordination overhead and implementation feasibility. Standards-based mechanisms and programmable Open RAN architectures can support deployment, but they should be distinguished from the underlying mitigation algorithms.

Overall, no single technique is universally superior for B5G networks. Technique selection should depend on the interference scenario, network density, available information, response-time requirements, computational capacity and acceptable coordination overhead. Future research should prioritize scalable, low-complexity and deployment-oriented schemes that achieve measurable interference-control gains with reduced computational and signaling requirements under realistic B5G operating conditions.

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