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A COMPREHENSIVE REVIEW OF DEEP LEARNING-BASED (DL) APPROACHES FOR INTERFERENCE MANAGEMENT IN 5G NETWORKS

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ABSTRACT

The deployment of fifth-generation (5G) mobile networks is characterized by the increased level of infrastructure complexity, which aggravates the problem of interference distortion. Interference significantly degrades signal quality, decreases network capacity, reduces coverage, and deteriorates the Quality of Service (QoS) and user experience. The application of Deep Learning (DL) offers a promising approach to addressing interference management problems in 5G networks, owing to the ability of DL algorithms to learn hidden patterns underlying interference generation. Nevertheless, majority of this studies concentrate on particular aspects of interference management, and separate research groups investigate diverse problems, using different deep learning models, categorizing interference in diverse ways, and implementing various management functions. The purpose of this study is to synthesize the current knowledge on interference management based on deep learning approaches in 5G networks. The classifications covers neural network architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Deep Reinforcement Learning (DRL), and Autoencoders (AEs); interference categories, including co-channel, adjacent-channel, cross-tier, and multipath interference; management functions, such as interference detection, prediction, and control; and deployment scenarios, including massive Multiple-Input Multiple-Output (MIMO) systems, millimeter-wave (mmWave) networks, heterogeneous networks, Device-to-Device (D2D) communication, Unmanned Aerial Vehicle (UAV)-assisted networks, and Intelligent Reflecting Surface (IRS)-assisted communication systems. In addition, the review examines the current solutions and their limitations in detail. The key finding of this study is that the majority of the papers address isolated functions of interference management, missing the concept of closed-loop interference management systems. Most of the reviewed articles do not consider the mobility of users and networks, have a high computational complexity, are not generalized enough to operate in multiple scenarios, and do not consider the problem of multiple types of interference. Based on the findings of the review, several directions for future research on deep learning-based interference management in 5G networks were proposed.

Keywords: Fifth Generation (5G); Deep Learning; Interference Management; Interference Detection; Interference Prediction

1. INTRODUCTION

The deployment of Fifth Generation (5G) mobile communication system started a pivotal era in wireless technology, driven by the necessity to accommodate increased user requirements such as

ultra-low latency communication, massive input and output type communication, and high-speed connectivity (Yang et al., 2024). However, the increased complex nature of 5G infrastructure, which is characterized by heterogeneous networks, high frequency, multi-tier small cells, and multi-meter frequency waves, introduced several distortion issues. Distortion is degrading in signal quality during its journey from transmitter to receiver (Maheswari and Padmaja, 2024). It is characterized by noise, interference, nonlinear impairment, channel fading, and jitter which often affect general service quality in 5G networks (Ma et al., 2024). Addressing this challenge in real time underscores the need for smart quality of service management for 5G network.

Distortion stems from several sources in 5G networks such as the nonlinearity of signal behavior, multipath propagation, radiation frequency, and dynamic interference in dense urban environments (Alzubaidi et al., 2022; Sanchez et al., 2021). This distortion affects 5G networks massively due to their dependence on narrow time slots, making them vulnerable and affects quality of service such as throughput, losses and user experience (Alzubaidi et al., 2022).

Over the years, several studies have been presented to address distortion challenges in 5G network. For instance, Maheswari and Padmaja, (2024) applied source coding, channel coding and inter frame predicting method of independent predicted frames for the management of delay in 5G radio, but focused on video latency as distortion type considered. Sanchez et al. (2021) proposed a fluctuating multipath fading model for evaluating communication quality in 5G network. Wu (2022) proposed novel Reconfiguration Intelligent Surface (RIS) for adaptive wireless physical environment. The distortion considered in the study is multipath fading stemming from dynamic user behavior. The RIS coated on the reflector could mitigate multipath fading. Osama et al. (2021) proposed a new soft frequency reuse scheme to mitigate interference in the distortion of 5G network. The model operated by switching cells based on the contribution of interference. In the same vein, Deep Q Learning (DQL) was proposed by Warriar et al. (2023) for interference management in 5G powered quadcopter, while collaborative learning was applied by Mohammed et al. (2024) for interference management. This was achieved through the application of beam forming and DQL. The beam forming steers the antenna to area with less intelligence while the DQL controls the phase shifter of the base station.

While these approaches have all contributed to migration of different distortion sources in 5G network, there is need for a proactive model which can be adaptive to dynamic and highly dimensional behavior of distortion such as interference in 5G network. Among the different distortion types, Marzban et al. (2023) identified interference as a major challenging factor which has negative consequences on the capacity and performance of wireless network system. The author seconded that high interference on network results to reduced signal to interference plus noise ratio, which in turn reduces the coverage of the network, degrade link quality of service and impact on overall user experience. To this end, this work proposes a DL-based approach to interference distortion management in 5G network using hybrid adaptive approach. DL unlike traditional machine learning models, provide extremely high accuracy in solving pattern recognition problem (Mubarak, 2022; Ebere et al., 2025). It is adaptive to learn dynamic data and

have continued to gain increased research interest in the telecommunication sector (Chidi et al., 2024).

In context of interference in 5G networks, deep learning has been applied by several researchers like Osman et al. (2021) who trained one dimensional (1D) CNN for interference detection and recorded 1.47 mean absolute error on IoTG-CUE dataset. Marzban et al. (2023) proposed DL for probabilistic interference prediction in mmWave network. The study only detects distortion but did not control it. Sejan et al. (2024) proposed RNN for co-channel interference management. Several models such as Long Short Term Memory (LSTM), Bidirectional-LSTM (Bi-LSTM) and gated recurrent unit were popular RNN considered for the work. Experimental results identified Bi-LSTM as the best, but stopped at detecting the problem without controlling it. Distortion is a complex problem which requires tracking, detection and control, to completely manage it. Hence, there is need for a solution which can help arrest this problem in 5G network holistically. To achieve this, our study explores the application of deep learning-based models for real-time management of interference distortion in 5G network using hybrid adaptive technique.

2. REVIEW OF RELATED WORKS

In the study presented in AlSheyab et al. (2020), interference was analyzed due to the use of small cells in conjunction with Network Flying Platforms (NFPs) by taking into account the related system constraints. The researchers used bipartite matching and local search-based optimization algorithms, focusing on the Hungarian-Based Initial Minimum Total Interference (HBIMTI) algorithm to provide fairness among small cells and to reduce the total interference. Reduction in computational complexity and approach to the computational solutions, near to the optimal ones, were obtained by the proposed techniques. The simulations also showed a significant decrease in the level of interference in the network. In the practical 5G and beyond communication scenarios, however, the mobility and power consumption of NFPs were not taken into account, and these important features may impact the level of interference and system performance.

Nakamura et al. (2019) has investigated the intra-channel interference in millimeter-wave mesh backhaul networks for various interference management techniques. These comprises of the deployment of millimeter-wave access points, orthogonal channel allocation, optimal transmission power allocation, etc. The proposed approach successfully reduced interference situations, especially when no route multiplexing was used, where interference was reduced in a region of about 250 metres from the millimeter-wave gateway. The results showed that efficient channel and power allocation was crucial to optimize the network performance but this proposed approach had not been tested in a real-time communication setting, so it is difficult to confirm the effectiveness of the approach in real-time communication settings with dynamically varying network conditions. Ge et al. (2023) explored collaborative and distributed approaches for coordinated beamforming in massive MIMO cellular networks. The researchers used distributed beamforming methods to enhance the ability to manage interference, and lessen reliance on centralized network control. The results indicated that the distributed method decreases the need for centralized Channel State Information (CSI), which benefits communication overhead and makes massive MIMO networks

more scalable. Benefits of this are not enough to compensate for the fact that the study did not include an intelligent mechanism for real-time tracking of and detection of signal distortion. This restriction has led to the need for adaptive intelligent techniques which can continuously sense interference and reconfigure the beamforming parameters to adapt with the network conditions.

Yeong and Srikrishnan (2024) proposed an intelligent interference mitigation technique based on a Deep Q-Network (DQN) agent and two new models: Long Short-Term Memory (LSTM) and collaborative beamforming. The DQN agent was employed to find the angles related to interference, and beamforming was employed to optimize the performance of the antenna. The method was effective in adaptively reducing interference and enhancing the Signal-to-Interference-plus-Noise Ratio (SINR) in the context of adaptive beamforming. The study however did not take into account the co-channel and adjacent-channel interference which are significant factors in real cellular networks causing signal degradation. Furthermore the developed model was not easily generalizable for different situations, suggesting the need for a more powerful and flexible interference mitigation framework.

Byun et al. (2019) studied the phenomenon of cross-tier interference in cellular networks with small mobile cells. The researchers chose small-cell user equipment with dominant channel space and minimum rank as well as used Zero-Forcing Beamforming (ZFBF) to combat interference. The simulation results demonstrated that the developed approach enhanced the performance of the users served by macro cells and small cells. This showed the superiority of spatial processing and user selection for minimizing cross-tier interference. However, the effect of interference increased as the cell size became larger. This restriction highlights the importance of interference mitigation methods that will be able to sustain good performance for different cell sizes and network configurations.

In this regard, Nasser et al. (2019) explored interference mitigation and power allocation of downlink MIMO-NOMA heterogeneous networks. To tackle the co-tier and cross-tier interference, the researchers advocated an interference alignment and coordinated beamforming technique using power allocation. The method was developed using the power allocation, interference alignment and coordinated beamforming techniques to enhance the network performance. It was found that this evaluation showed differences between the system sum-rate and outage probability with the conventional OMA and NOMA schemes, and the assisted schemes using existing interference alignment and coordinated beamforming techniques showed an improvement in the system sum-rate at high SNR levels compared to the sum-rate of the proposed scheme. The approach proved to be successful in integrating power allocation and beamforming to mitigate interference, but the computational complexity was fairly high. The complexity may also restrict the ability to deploy in real-time, especially within dense and dynamic heterogeneous networks.

Xu et al. (2018) studied how interference can be managed in Device-to-Device (D2D) communication in multi-tier heterogeneous cellular networks. The study analyzed three communication modes: D2D, small-cell, and macrocell communications for good coordination of the transmission and interference control. The proposed scheme was able to reduce unwanted signals between the links in the transmissions and kept the Quality of Service (QoS) adequate. The

results showed the feasibility of using coordinated communication modes in order to enhance the spectrum utilization and network performance. D2D users' mobility, however, was not taken into account. User mobility has a significant impact on the characteristics of the channel and the interference pattern and therefore would add to the practical applicability of such techniques to include mobility.

Arjoun and Faruque (2022) studied machine learning application to beamforming optimization in mm-wave massive MIMO communication system. The researchers concentrated on an experience-driven learning approach for beam-pattern prediction, beam selection and user localization. The proposed method proved its capability of adaptability and flexibility with varying communication environments and highlighted the potential of machine learning in the optimization of beam selection and resource allocation but did not take into account the multi-dimensional interferences and distortions in massive MIMO. In addition, the model did not have much capacity to transfer to other settings. This gives rise to the requirement of intelligent models that are able to deal with high-dimensional interference characteristics, under different network conditions, with reliable performance.

Chen et al., (2020) presented an approach of hybrid beamforming with the help of machine learning in millimeter-wave MIMO (mm-Wave MIMO). The convergence of the beamforming optimization and architectural flexibility were enhanced by using an autoencoder-based neural network architecture. The proposed approach improved the adaptability of beamforming/combining process and showed that some of the computational burdens of the traditional optimization approaches can be mitigated by the use of neural networks. The study did not take into account interference from co-channel and adjacent channels. However, this restriction can impact the effectiveness of the technique in crowded wireless settings with the presence of multiple types of interference. Hence, the need for intelligent beamforming techniques that can take into account various interference sources for optimization.

In distributed MIMO systems, Kaur (2024) explored adaptive beam scheduling and localization methods that leverage machine learning to enhance network performance and utilization. The near-field localization accuracy using beamforming with location information under varied channel conditions was enhanced. The results showed that user location information can help a wireless system focus the beam more effectively and accurately, and allocate resources more effectively, between users. In very dynamic environments, the proposed method suffered from performance loss. If the user position, channel conditions, and interference change quickly, the reliability of the beamforming decisions might be decreased. The restriction highlights the importance of intelligent real-time tracking and prediction methods that can provide good beamforming in highly dynamic network environments.

To enhance the security and efficiency of wireless communication networks, Zhang et al., (2023) studied the combination of beamforming and Intelligent Reflecting Surfaces (IRS) with the help of deep reinforcement learning. The proposed scheme aimed to synchronize communication and beamforming while enabling cooperative jamming and physical-layer security for IRS. The results indicated better energy efficiency, and revealed the possibility of using IRS-aided beamforming to

increase the security of communication. Coordinating the parameters of IRS phase shifts and beamforming in real]

time added significant computation complexity. In this limitation, there is a need for computationally efficient intelligent algorithms which jointly optimize IRS configurations and beamforming parameters under rapidly varying network and interference conditions.

3. CLASSIFICATION OF DEEP LEARNING APPROACHES FOR INTERFERENCE MANAGEMENT

The explosion of Deep Learning (DL) applications within 5G interference management has generated a plethora of heterogeneous literature with different network architectures, interfering signals considered, and scenarios analyzed. Table 1 provides an overview of all the papers discussed in this chapter categorized according to (i) deep learning architecture (ii) interference type (iii) management function and (iv) network deployment scenario. Furthermore, this classification highlights areas within the scope of interference management where none of the existing works address, hence providing justification for hybrid adaptive approaches.

Table 1: Classification of DL Approaches by Architecture

Architecture Class	Core Mechanism	Primary Application
Convolutional Neural Networks (CNNs)	Spatial feature extraction from spectral and channel data	Interference detection and classification
Recurrent Neural Networks (RNNs)	Temporal sequence modelling for interference dynamics	Interference prediction and temporal tracking
Deep Reinforcement Learning (DRL)	Trial-and-error policy optimization for control decisions	Adaptive beamforming, power control, IRS configuration
Autoencoder-based Networks	Unsupervised feature learning and dimensionality reduction	Hybrid beamforming and combining optimization

3.1 Classification According to Deep Learning Architectures

The type of neural network model determines the functionalities and features of the interference management system. From the surveyed works, four major DL architectures were found to be frequently utilized. These include;

The CNN approach of Osman et al. (2021) makes use of one-dimensional convolutional layers to process the spectral inputs for interference identification and reaches a mean absolute error of 1.47 on the IoTG-CUE dataset. Nevertheless, CNNs are not suitable in scenarios where temporal effects are relevant since they can only model short-term temporal dependencies. In contrast, the RNNs' variations, including LSTM, Bi-LSTM, and GRU, claim to capture long-term temporal patterns. Sejan et al. (2024) compared these RNN variations for co-channel interference management and found that Bi-LSTM was the best-performing network. Mohammed et al. (2024) utilized LSTM networks within a DRL framework to learn temporal interference patterns. Overall, while RNNs

variations excel at temporal pattern recognition, they are not suitable for closed-loop interference management.

The DRL-based interference management is the most common research direction, allowing the implementation of closed-loop interference management without building a mathematical model of interference. Mohammed et al. (2024) proposed a DQN agent, which manages interference by varying the angle between the transmitter and receiver, while beamforming techniques were used to adjust the antennas' performance. Similarly, Warriar et al., (2023) employed the DQL algorithm for interference management in quadcopters, while Zhang et al., (2023) proposed a framework of deep reinforcement learning for IRS-assisted beamforming. The common drawback of the DRL approaches is their complexity, specifically when dealing with large action spaces, resulting in long training times. Another approach to interference management is autoencoders, which were used by Chen et al. (2020) to learn the channel state information encoding and decoding process for hybrid beamforming and combining. While the autoencoder-based approach can improve the system's performance, it is more of an optimization than a management technique.

3.2 Classification by Interference Type

There are various sources of interference in 5G networks that require different management techniques. The interference varies depending on the technology, location, and time. The survey results showed that most of the research addressed only several types of interference, and only a few works tried to provide a generalized overview of interference management. Specifically, Table 2 demonstrates the interference type covered by the reviewed articles.

Table 2: Classification by Interference Type Addressed

Interference Type	Description	Studies Addressing This Type
Co-channel interference	Signals on identical frequencies from neighbouring cells	Nasser et al., (2019); Xu et al., (2018); Sejan et al., (2024)
Adjacent-channel interference	Spectral leakage from neighbouring frequency channels	Nasser et al., (2019) (partial)
Cross-tier interference	Interference between macrocells and small cells	Byun et al., (2019); AlSheyab et al., (2020); Nasser et al., (2019)
Intra-channel interference	Self-interference within the same channel	Nakamura et al., (2019)
Multipath fading	Signal distortion from multiple propagation paths	Sanchez et al., (2021); Wu (2022)

A notable finding from Table 2 is the lack of studies addressing co-channel and adjacent-channel interference simultaneously using hybrid autoencoders. For instance, authors of Chen et al., (2020) acknowledged this research gap while developing an autoencoder-based hybrid precoder. On the other hand, Mohammed et al., (2024) addressed it partially and demonstrated that interference could be mitigated effectively in hybrid beamforming systems. However, co-channel, and adjacent

channel interferences are particularly disruptive in dense urban 5G environments and should be jointly treated.

3.3 Classification by Management Function

For managing interference in hybrid beamforming systems, there is a set of required functions ranging from detection to prediction and control as shown in Table 3.

Table 3: Classification by Management Function

Functional Layer	Objective	Limitations
Detection	Identify presence and source of interference	Passive; no mitigation action
Prediction	Forecast future interference patterns	Proactive but lacks control mechanism
Control/Mitigation	Actively reduce or eliminate interference	Often reactive; limited adaptability
Holistic Management	Integrated detection-prediction-control	—

The reviewed articles can be sorted according to the main topic. Most of them address interference detection and prediction, whereas only a few studies emphasize the direct control and prediction of interference. This fact is illustrated in Figure 1.

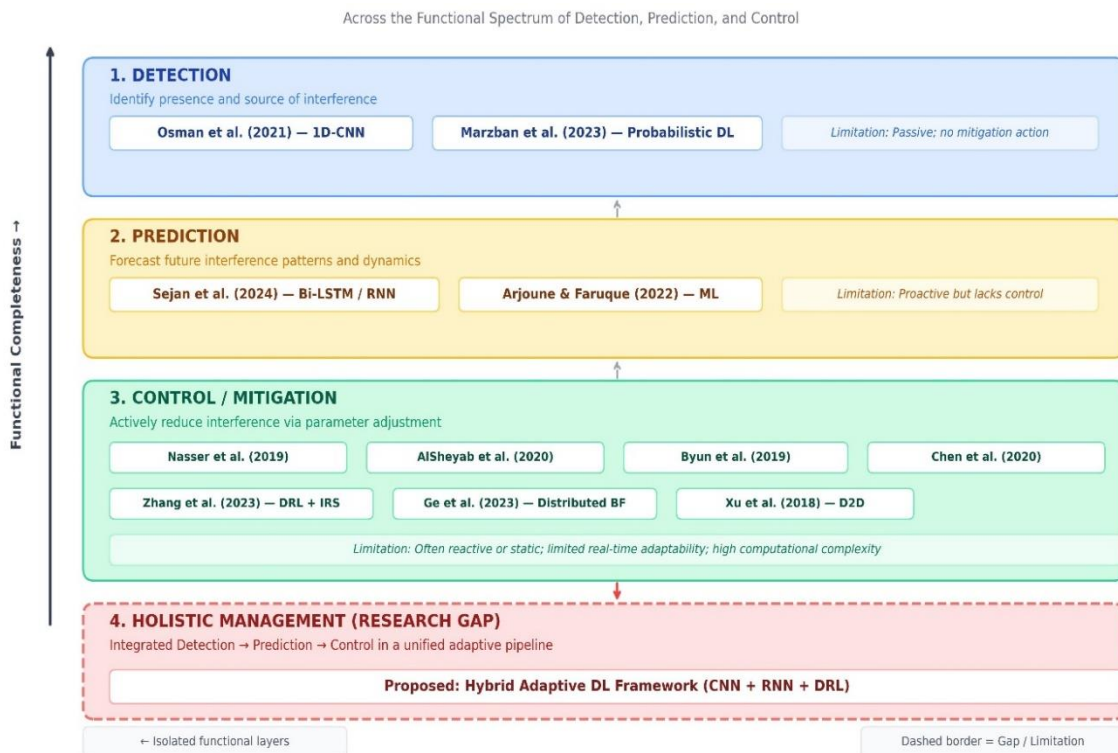


Figure 1: Stratification of DL-Based Interference Management Approaches

Detection Layer: The literature survey shows that most studies focus on developing supervised learning approaches for interference detection. For instance, Osman et al. (2021) trained a 1-D CNN to detect the existence of interference, whereas, Marzban et al., (2023) designed a DL-based approach to predict the probability of occurrence of interference in millimeter-wave networks. Similarly, the majority of the published articles concentrate on elaborating the potential of DL approaches for interference detection and awareness. Nevertheless, the studies do not go beyond the detection stage since they only address the prediction layer and stop at the identification of the presence of interference. The prediction layer is the basis upon which the control layer is built. For example, Sejan et al., (2024) found out that using a Bi-LSTM DL model could predict co-channel interference patterns better than the traditional recurrent neural networks. However, the authors agree that the DL-based framework only identifies interference patterns but does not go further and propose a control mechanism to counteract the detected interference.

Control Layer: The control layer comprises studies that propose frameworks or mechanisms for altering network parameters to counteract interference. Mohammed et al., (2024) designed a DQN-enabled collaborative beamforming approach by integrating deep reinforcement learning with collaborative beamforming to reconfigure the phase shifters in a realistic radio access network. Nasser et al., (2019) proposed an interference alignment with coordinated beamforming based on power allocation. AlSheyab et al., (2020) suggested a novel framework that uses bipartite matching and local search algorithms to balance the aggregate interference in small cell networks with Network Flying Platforms. On the contrary, most of the discussed articles do not incorporate deep learning approaches to enhance the tracking and prediction of interference levels in a closed-loop system.

Notably, no reviewed study achieves a seamless integration across all three functional layers and this detection-prediction-control discontinuity represents a fundamental structural gap in the current literature.

3.4 Classification by Network Deployment Scenario

The applicability of an interference management technique is heavily contingent upon the specific 5G deployment scenario. Table 4 shows the classification of network deployment scenario according to their target network environment.

Table 4: Classification by Deployment Scenario

Deployment Scenario	Characteristics	Primary Technique
Massive MIMO Cellular Networks	Large antenna arrays, spatial multiplexing	Distributed/coordinated beamforming, ML-based beam selection
Millimeter-Wave (mmWave) Systems	High frequency, directional beams, susceptibility to blockage	Channel allocation, hybrid beamforming, probabilistic prediction

Heterogeneous Networks (HetNets)	Multi-tier architecture (macro, small, femto cells)	Power allocation, ZFBF, bipartite matching
Device-to-Device (D2D) Communication	Direct UE-to-UE transmission, spectrum reuse	Communication mode coordination
UAV/Network Flying Platforms	Aerial base stations, high mobility, dynamic topology	HBIMTI, DQL
IRS-Assisted Networks	Programmable wireless environment, passive beamforming	Deep RL, RIS coating optimization

Several scenario-specific limitations emerge from the reviewed literature. While Ge et al., (2023) proposed a solution to reduce the dependence on centralized Channel State Information (CSI) in massive MIMO networks, the study did not consider integrated real-time interference tracking. Similarly, Kaur's (2024) solution to optimize beam scheduling via location-aware machine learning underperformed in highly dynamic environments, and Xu et al., (2018) designed an efficient interference management approach for device-to-device (D2D) communications but neglected the mobility dimension entirely, which is particularly surprising given the inherently mobile nature of D2D links. Overall, the combination of these scenario-specific limitations serves as the primary justification for this research.

4. COMPARATIVE ANALYSIS AND DISCUSSION

This section presents a comparative analysis and discussion of the classification findings. In particular, the performance trade-offs made by the reviewed solutions were analyzed, and research limitations that have triggered the current investigation were identified. For this purpose, Table 5 gives a comparison of the key studies on the six critical dimensions: interference reduction performance, computational complexity, real-time applicability, generalization, mobility support, and overall functional completeness (that is., presence of detection-prediction-control modules).

Table 5: Multi-Dimensional Comparative Analysis of Key Studies

Study	Interference Reduction Performance	Computational Complexity	Real-Time Applicability	Generalization	Mobility Support	Overall Functional Completeness
AlSheyab et al. (2020)	High (near-optimal)	Moderate	Limited	Low	No	Control only
Nakamura et al. (2019)	Moderate-High	Low	Not validated	Moderate	No	Control only

Ge et al. (2023)	Moderate	Low-Moderate	Partial	Moderate	No	Control only
Mohammed et al. (2024)	High	Moderate	Partial	Low	Limited	Prediction + Control
Byun et al. (2019)	Moderate	Low	Yes	Moderate	Yes	Control only
Nasser et al. (2019)	High	High	No	Low	No	Control only
Xu et al. (2018)	Moderate	Low	Yes	Moderate	No	Control only
Arjoune and Faruque (2022)	Moderate	Moderate	Partial	Low	No	Prediction
Chen et al. (2020)	Moderate	Low	Yes	Moderate	No	Control only
Kaur (2024)	Moderate	Moderate	Partial	Low	Yes (but degrades)	Prediction + Control
Zhang et al. (2023)	High	High	No	Low	No	Control only
Osman et al. (2021)	N/A (detection only)	Low	Yes	Moderate	No	Detection only
Marzban et al. (2023)	N/A (prediction only)	Low-Moderate	Yes	Moderate	No	Prediction only
Sejan et al. (2024)	N/A (prediction only)	Moderate	Yes	Moderate	No	Prediction only

The comparative analysis unveiled several research trends. First, most works that demonstrated excellent interference elimination performance suffered from high computational complexity or lack of practical implementation for dynamic networks. For example, the algorithms proposed by Nasser et al. (2019) and Zhang et al. (2023) achieved outstanding results; however, their performance came at the expense of increased computational complexity. In contrast, the low-complexity methods proposed by Byun et al. (2019) and Chen et al. (2020) demonstrated relatively lower performance in their respective evaluations.

Second, generalization ability appeared as a significant challenge in the reviewed works. Mohammed et al. (2024), Arjoune and Faruque (2022), and Kaur (2024) noted limitations in their methods' ability to perform consistently well in different environments. Such shortcomings are unacceptable in the case of 5G networks because modern wireless systems operate in a variety of radio environments, from urban macrocells to rural microcells. Third, most articles made little or no attempt to account for mobility. With the exception of Byun et al. (2019) and Kaur (2024), the majority of the reviewed articles did not consider channel mobility at all. At the same time, Kaur's algorithm demonstrated fragile performance in the case of highly dynamic channels. AlSheyab et al. (2020) and Xu et al. (2018) explicitly stated that their solutions were oblivious to mobility, which significantly limits their applications in practice.

5. CONCLUSION

In this review, we analyzed the application of deep learning (DL) in interference management for 5G networks. In particular, we grouped together existing DL-based approaches according to the architecture, type of interference, functions performed, and scenarios. Modern DL literature demonstrates promising trends in applying CNNs for spatial-spectral detection, RNNs (specifically, Bi-LSTM) for temporal prediction, and DRL for learning optimal control policies in the form of beamforming and power allocation.

Nevertheless, the current research trend also has a number of shortcomings. First, most works concentrated on a limited set of functions, i.e., detection only, prediction only, or control only, while ignoring other aspects of the problem. Second, few solutions simultaneously considered both co-channel and adjacent-channel interference. Third, only a few articles accounted for mobility in their solutions. Fourth, no works explicitly addressed the need for real-time validation of interference management algorithms in practice. Fifth, most articles ignored the requirements of ultra-reliable and low-latency communication (URLLC). These shortcomings are significant challenges to solving interference management in 5G networks as the density of radio access networks increases, and 6G standards are developed.

5.1 Future Research Directions

Based on the research trends identified in this review, we propose a list of recommendations for future research in the field of DL-based interference management for 5G networks.

1. Hybrid adaptive approaches: A promising research direction is to combine multiple network architectures into a single DL model that would incorporate closed-loop feedback. For example, CNN can be employed for spatial-spectral detection, while Bi-LSTM can be used for temporal prediction. These two elements can be connected via a DRL agent that would perform beamforming and power control.

2. Joint Optimization of Multiple Types of Interference: The overwhelming majority of works addressed only one type of interference, primarily co-channel interference. However, in practice, networks are subject to multiple types of interference, including adjacent-channel, cross-tier, and multipath. Therefore, it is critical to develop models that simultaneously account for multiple types of interference.

3. Methods with Generalized Performance: Most authors concluded that their methods' performance was significantly affected by mobility and channel conditions. Nevertheless, little effort has been made to generalize the performance of DL algorithms across various environments. One promising approach is to employ meta-learning or federated learning to adapt DL algorithms to new environments without substantial redesign.

4. Development of methods with reduced complexity for real-time implementation: Many works demonstrated that DL algorithms for interference management have high computational complexity. This feature significantly challenges their application in practice. To reduce complexity, researchers should consider alternative approaches, such as model compression, neural architecture search, or native implementation in AI-RAN.

5. Standardized open datasets: The reviewed articles rarely described their datasets in detail, and there were no open datasets available for experimentation. To advance the field, researchers should propose standardized open datasets with annotated data.

6. Implementation within O-RAN framework: The O-RAN framework is the future of telecommunications because it promotes openness and interoperability of network equipment. Therefore, DL research on interference management should consider how their methods can be implemented in O-RAN, particularly in the near real-time RIC through xApps and rApps.

7. Explainable AI: Most DL methods for interference management are black-box, which challenges their adoption in practice due to a lack of interpretability. Therefore, researchers should consider XAI methods that allow for explaining the behaviour of DL models.

8. Semantic communication in AI-native 6G networks: Semantic communication can be an interesting research direction for interference management in AI-native 6G networks. Such networks will inherently utilize AI for radio resource management, including interference management. Therefore, it is promising to explore semantic communication from the perspective of interference management.

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