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RESEARCH ARTICLE

Interference Mitigation in 5G Networks: Review, Challenges, and Deep Learning-Based SIC Framework

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Abstract

The fifth generation (5G) network represents an advancement in mobile communication technology in a region with increasing demands in usage to solve the problem of traffic congestion, high latency, and low speed. However, interference is one of the major limiting factors that degrades the 5G network performance. The adverse effects of interference have led to several research studies into mitigation techniques for 5G networks. This paper presents a comprehensive review of interference types and mitigation techniques in 5G networks, including conventional approaches such as power control, inter-cell interference coordination, beamforming, and resource allocation. Moreover, this work provides an analytical framework for Deep Learning (DL)-Based Channel Estimation and Successive Interference Cancellation (SIC) in 5G non-orthogonal multiple access (NOMA) systems. This study extends existing models by incorporating residual interference modeling, highlighting the impact of error propagation in SIC systems. This paper synthesizes existing techniques, identifies key research gaps such as: imperfect channel estimation as in the conventional SIC, failure to address the error components caused by the residual interference that is often adhered to SIC technique, and establishes a unified perspective on integrating DL into interference mitigation, showing that DL-Based SIC has strong potential for improving interference resilience. We believe that our proposed technique will serve as guidelines for moving forward with SIC aware protocol research in 5G and Beyond 5G networks.

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Keywords: Channel Estimation; NOMA; Successive Interference Cancellation (SIC); Deep Learning (DL); Interference Mitigation.

1. Introduction

5G cellular networks and beyond require massive connectivity, high speed, as well as low latency. Several researchers have made rigorous efforts to proffer solutions to the problem of traffic congestion due to increasing data request, massive connectivity and the scarcity of radio spectrum in sub-6 GHz. The aforementioned solutions depend on either the new signal processing techniques, densification of the network, or additional frequency bands exploitation. Due to the large bandwidth, mmWave communication is affected by large free-space path-loss more than the sub-6 GHz networks. In addition, attenuation is prominent in some mmWave bands due to atmospheric absorption, rain, and snow effects, thereby limiting its applications to only a shorter distance (i.e indoor systems). For outdoor applications, the transmission power must be increased by using directional antennas with high gain. In dense deployments, one of the major challenges faced by 5G and Beyond 5G (B5G) networks is interference, which reduces signal quality, causes transmission errors, and packet losses. However, DL-based SIC is emerging as a powerful solution for interference management in 5G, B5G, and 6G networks. By leveraging DL to learn complex signal and channel characteristics, it will overcome many limitations of conventional SIC, including sensitivity to channel estimation errors, non-linear distortions, and error propagation. Since 5G and B5G networks aim to support many users within limited resources, DL-based SIC improves the separation of simultaneously transmitted signals, enabling more efficient spectrum re-use. This thereby increases overall network capacity and throughput. The Internet of Things (IoT) will be established by the network as an essential part of day-to-day activities, through the foundation laid to unleash its full potential. More importantly, modern mobile devices such as smartphones and tablet computers provide multi-core processors and graphics processing cores, which open up new applications in the aspect of Augmented Reality (AR) and Virtual Reality (VR) technologies [1]. The 5G network architecture comprises device-to-device (D2D) communication, which introduces advancements in spectrum efficiency, energy efficiency, total system capacity, and higher data speed [2]. The 5G wireless communication systems have now been widely standardized and marketed after years of research and development.

2. Background

2.1. 5G Network Enablers

The advent of 5G technology has considerably helped societies and promoted a plethora for academic studies. In communication networks, 5G technology is made possible by a few key enablers some of which are shown in Figure 1.

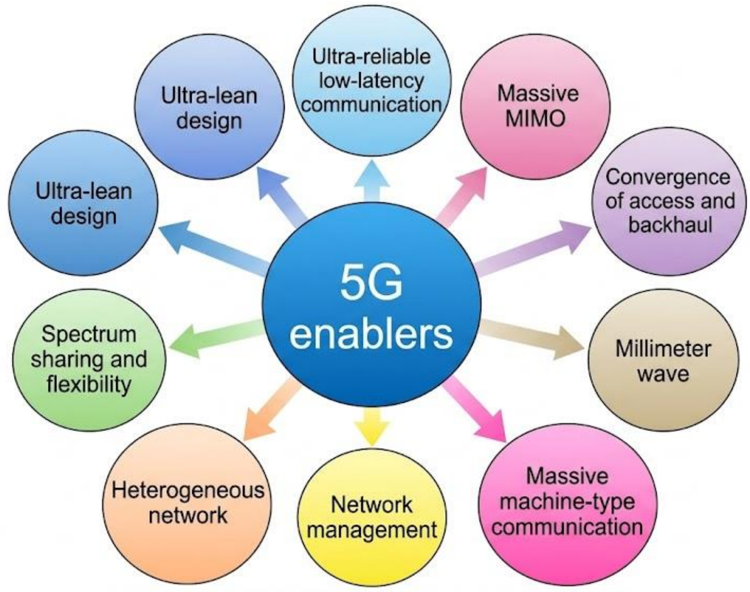


Fig. 1. 5G Network enablers.

Each enabler has various characteristics, and the integration of these technologies forms the foundation of 5G systems [2]. Due to the number of devices adopting wireless and IoT technologies that is dramatically rising, Heterogeneous Networks (HetNets) which are networks that integrate various cell types and access methods, provide solutions to the problem of the increase in demand for network usage. Massive Multiple-Input-Multiple-Output (MIMO) technology is another crucial 5G enabler, which increases data rates, while reducing interference by employing the beamforming technique to focus signals on one another [3]. Future 5G technology is expected to utilize an ultra-lean architecture, where "always on" signals are minimized to create an efficient network at a low operational cost. By adopting an ultra-lean design, network transmission can be reduced without compromising the delivery of user data [4]. An ultra-low latency enabler, like the one in [5], can decrease processing times and transmission intervals while also increasing the bandwidth of the radio resource blocks in which a specific amount of data is transmitted. Since the direct communication link (also known as D2D) provides low-latency transmission for nearby devices, it may help prevent queuing delays at the radio transmitter. In order to attain zero overhead communication, 5G technology requires facilitators that simplify device connection states and provide channel access with less signaling. The introduction of Massive Machine Type Communication (mMTC) 5G network deployment—a next-generation mobile network—was made feasible by the use of IoT concepts. Network management is one of the most critical issues in any communication technology. Self-Organizing Network (SON) management in 5G was recognized as the main driving force behind advancements in operations, administration, and management duties with little human intervention [6]. With the combination of access and back-haul, wireless communication between radio network nodes can be established with ease. An alternative is to employ convergence rather than simply optical fiber. In [7], the 5G transport network architectural options and scenarios were explained based on several standards and previous studies, the problems of existing infrastructures of developing countries were investigated, and new proposed technologies that may help to address those challenges were put into consideration. To address the spectrum scarcity issue in order to implement 5G architecture, one of the techniques being researched in several studies is millimeter-wave (mmWave). The mmWave frequency range spans an ultra-high frequency from 30 GHz to 300 GHz [8]. With extremely high data rates, ultra-high capacity, very large bandwidth, and very low latency, it provides new services and economic sectors that may benefit from 5G. When it comes to addressing spectrum scarcity and making use of the spectrum band for 5G technology, spectrum sharing (SS) and flexibility are two of the most important challenges that need to be overcome. By enabling many users with different choices to share the same frequency band without interfering with one another, SS optimizes the utilization of the available spectrum [9].

2.2. 5G Network Architecture

5G network architecture is a flexible, service-based framework defined by the 3rd Generation Partnership Project (3GPP) under the designation 5G NR (New Radio), as shown in Figure 2. It is designed to accommodate enhanced Mobile Broadband (eMBB), Ultra-Reliable Low Latency Communication (URLLC), and Massive Machine-Type Communication (mMTC). The overall layout consists of User Equipment (UE), gNB RAN (Radio Access Network), and the 5G Core Network. The challenges of 5G back-haul networks are crucial for traffic evacuation in indoor and outdoor environments [10, 11]. Currently, literature has largely ignored these problems in a super-dense HetNet 5G network setting. Furthermore, there is not a framework for the architectural development of 5G networks that can systematically include most of the major enabling technologies.

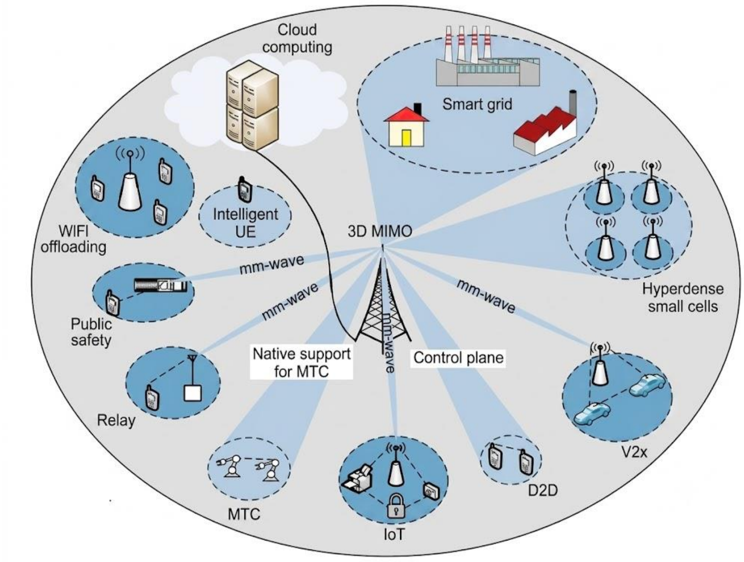


Fig. 2. 5G Network architecture.

2.3. 5G Network Enablers

The advent of 5G technology has considerably helped societies and promoted a plethora for academic studies. In communication networks, 5G technology is made possible by a few key enablers some of which are shown in Fig. 1.

2.4. Classification of Interference

Interference is a basic and inescapable occurrence that has an impact on the performance of 5G wireless communication systems. Some literature frequently discusses various forms of interference. It is important to remember that interference affects every kind of wireless network in different ways because of their varied transmission and deployment scenarios; the nature and manner of interference may therefore vary between wireless networks. The major types include:

- C**o-channel interference:** Multiple wireless systems operating at the same frequency on the same channel cause this occurrence, which is also named crosstalk interference. It goes against the core concept of 5G systems, which seek to maximize frequency reuse to support many users on the same spectrum [10]. Increased competition between devices using the same channel causes signal fading and lower throughput, which are the main effects of co-channel interference (CCI).
- **Adjacent channel interference:** It is the product of an undesirable signal in the adjacent frequency band of the desired signal's coverage region. By broadcasting at a frequency on the channel, Base Station (BS) or macro-BS leaks signals to the frequency next to that band, creating adjacent channel interference (ACI), which is often experienced by 5G [11]. Ultimately, this interference is caused by leakages from inferior filters into the desired pass-band channel, which has an irreducible bit error rate (BER).
- **Inter-Symbol Interference:** This sort of interference relates to non-line of sight (NLOS) communication due to the multi-path effect [10]. Diffraction and scattering in the multi-path environment cause a variety of delays for signals reaching the receiver, which changes the speed of the signal pathway. Due to the delay spread, successive symbols overlap in 5G networks, resulting in a high level of inter-symbol interference (ISI).
- **Inter-Carrier Interference:** It is also connected to the NLOS communication system and the orthogonal frequency division multiplexing (OFDM) modulation technique. For efficient modulation, the OFDM sub-carriers are orthogonal to each other and very responsive to carrier frequency offset. The delay spread in the radio signal and the frequency offset at the receiver cause sub-carriers to lose orthogonality, which results in inter-carrier interference (ICI) [12].
- **Inter-Cell Interference:** A common issue for mobile cellular networks, inter-cell interference can reduce signal quality for edge users and restrict the overall network performance. It is usually brought on by competing cells utilizing the same resources [10]. Since tiny, low-power, low-complexity base stations (BSs) were extensively deployed within the macro coverage and limited spectrum resources were reused, ICI became increasingly severe.
- **Inter-beam interference:** Traffic signaling using beamforming is effective and visually appealing for 5G mobile networks. It functions with base stations as well as mobile devices [10]. To extend the transmission distance and make up for the attenuation loss that occurs while sending message signals, this approach is essential for mmWave communication. The spatial division of the several beams and the BSs in the neighboring cells, on the other hand, causes inter-beam interference.
- **Cross-Link Interference (CLI):** In the time-division duplex (TDD) system, the uplink and downlink communication are separated into different time slots while using the same bandwidth. The issue of cross-link interference (CLI) occurs when TDD systems are implemented, and the interference power is often considerably higher than the targeted signal [11]. The BS and UE interfere with each other when they transmit and receive in the same frequency range, lowering user throughput in accordance with the TDD principle. The uplink BS's downlink can sometimes be disrupted by another BS.
- **Inter-Numerology Interference:** One of the distinguishing features of 5G is its capacity to accommodate a range of sub-carrier numerology, such as 15, 30, 60, 120, and 240 kHz, which allows for versatility in supporting a wide range of devices and services, including mMTC, eMBB, and URLLC [12]. Because of the multiplexed sub-carriers' non-orthogonality, inter-numerology interference (INI) occurs when different devices and services employ different sub-carrier spacing.

Summarily, the different categories of interference that affect the key 5G enablers can be summarized as shown in Table 1 [11].

TABLE 1. Key 5G enablers and the types of interference that affect them.

5G Enablers	Description	Interference
HetNets	It is a conglomerate of different low-power cell types and access technologies.	ICI, Cross-tier interference, co-tier interference, control channel interference
MmWave	It operates on extremely high frequency (30-300 GHz). It provides high speed connectivity, larger data rates, spectral efficiency and reliability.	Multiple Access Interference (MAI), ICI and CCI
Massive MIMO	The base stations are equipped with very large number of antennas to improve spectral and energy efficiencies.	ICI, CCI, ACI
Full Duplex	It maximizes frequency usage by allowing simultaneous transmission and reception of signal over single spectrum at the same time.	Self Interference (SI), ACI, CCI
D2D Communication	It has the ability to connect to licensed and unlicensed spectra while enhancing capacity. So, it can connect multiple devices without using the core network.	Cross-tier interference, co-tier interference

2.5. Impact of Uplink (UL) and Downlink (DL) Asymmetry

Unlike previous generation, 5G UL and DL transmissions are inherently asymmetric. This asymmetry affects the interference distribution, channel estimation accuracy and SIC decoding order. In wireless communication, knowing the UL/DL imbalance is crucial for managing interference [13]. It serves as a roadmap for comprehending the kind of interference that is impacting the UE or BS and for knowing how to counteract it. Consequently, ML-based models trained on DL data may fail in UL scenarios, highlighting the need for domain-adaptive frameworks.

3. Literature Review

The deployment of the 5G mobile network has attracted serious research attention over recent years due to the increasing demand for network usage. However, as earlier mentioned, the 5G network performance can be seriously degraded by interference among other factors. Hence, several techniques have been proposed to improve its performance, which include Massive MIMO, Network Slicing, Mobile Edge Computing, and Beamforming. In [14], the authors proposed a Convolutional Neural Network (CNN)-based SIC model to replace conventional SIC. The neural network learned how to cancel interference more accurately under imperfect conditions. The approach improved sum rate and detection performance, although it did not validate massive user scenarios and dense heterogeneous networks.

In [15], the overview of the interference issues relating to the Beyond 5G (B5G) networks from perspective of HetNets et cetera was done. The proposed Deep Reinforcement Learning (DRL) algorithm is trained using an agent-based decision-making policy to attain the optimal solution for computational time, spectrum efficiency, and throughput. However, a test-bed measurement technique to validate the system's performance more realistically is highly required. An inter-user interference cancellation (IUIC) method focusing on the signal configuration and channel coding in 5G was proposed in [16]. The interference cancellation was achieved through user scheduling and adaptive modulation algorithms for 5G dynamic full-duplex cellular (DDC). Nevertheless, there is a need for refining the digital signal processing of the IUIC, user scheduling, and adaptive modulation algorithms, to further enhance Uplink throughput and Downlink throughput. Several other major interference cancellation types such as: Inter-cell Interference Cancellation (ICIC), Adjacent Channel Interference Cancellation (ACIC), Inter-Beam Interference Cancellation (IBIC) and so on, were not considered. Moreover, the novel technologies like Beam forming strategy, Massive MIMO and Machine Learning (ML) used in 5G and Beyond networks were not accounted for by the authors.

Signal processing was developed by [17] in which a pre-coding matrix was prepared for every user at base station with design of an equalization that is orthogonal to the pre-coding matrix. The result shows that the method works properly in the case of high-density users for interference mitigation, even though the channel capacity of the method performs low in the case of poor channel gain and low transmit power, and there is a need to consider multiple number of antennas at users' end. The measurement and performance analysis of signal-to-interference ratio (SIR) in wireless networks was reported in [18], which included evaluation of reliability and quality of service for different mobile networks. The measurement was carried out through intensive drive tests, and the network with better performance was stated. The researchers were not particular about the optimization technique suitable for the networks with poor performance. Interference mitigation approach using Massive MIMO (M-MIMO) towards 5G networks was carried out by [19] using game theory. The interference was mitigated through the introduction of feedback on the existing cell association and antenna allocation algorithms. However, an advanced approach is expected to be used to determine how often a user should take feedback data. In [20], analytical research was done on existing networks to be upgraded to 5G networks. Also, solutions were proffered to some challenges in implementation of 5G networks even though none of the interference cancellation techniques were addressed.

In a view to finding solution to the effect of noise on 5G network, Relativistic Average Generative Adversarial Network (RaGAN) was proposed in [21], which combines the bi-directional with long short–term memory (Bi-LSTM) model to reduce noise. The time-series data can be processed through this method, and the weighted loss function can be applied to formulate a noise mitigation model that suits radio communication signals, to ensure the source to sink removal of noise from radio signals. From the results, in comparison with the existing approaches, the proposed algorithm has caused the improvement of the noise reduction effect. The limitations of this method are that the signal was processed based on the time domain. Therefore, work needs to be done on deep learning technology in conglomerate with signal frequency domain to process signals. Additionally, the approach has major application in signal propagation on the Additive White Gaussain Noise (AWGN) channel; it needs to be applied to Rayleigh fading for verification of the practicability of this approach, to enhance the model's generalization ability.

A novel deep learning reinforcement algorithm using Artificial Intelligence (AI) was proposed in [22] to address the issue of interference through power control. The proposed solution effectively integrates unmanned aerial vehicles (UAVs) with 5G networks, cancels interference, and improves link performance, offering a significant advancement in this field. Despite that, the algorithm performs below average as far as novel technologies are concerned, and it has no previous information about the channel state which makes the channel estimates and associated training sequences irrelevant. The possibility of co-existence of Fixed Satellite Service (FSS) and 5G systems operating in the 3.5 GHz band with a restriction to the out-of-band emission index of 5G base stations was reported in [23]. The outcomes of the research highlight the protection margin needed for 5G systems to co-exist with FSS ground stations at distinct spacing frequencies, except that installing a radio frequency shielding network, fixing the filters for satellite earth stations, the limitation to the out-of-band emission index of 5G base stations, and the setting of isolation merging were not considered.

A Quality of Service (QoS)-based cooperative NOMA-aided group D2D system (Q-CNOMA) was presented in [24]. The method lessens the load on the group transmitter by sending the signal to a receiver in adjacent cells and as well enhances the total system performance. Modeling the main components in a D2D scenario as in receivers clustering around a transmitter requires that the spatial distribution of D2D transmitters should be modeled using a Gaussian–Poisson process (GPP). Despite this, works are yet to be done on selection of relay in the proposed Q-CNOMA system, to improve the system's performance. Interference mitigation in 5G network using frequency planning and Artificial Neural Network (ANN) was reported in [25], in which SIMULINK was employed to model a signal without interference and an interfered signal. The results obtained showed that the level of channel interference mitigation was higher with the application of ANN, compared to that of the frequency planning technique.

A review of beam-forming technologies for Tera-Hertz Ultra-Massive MIMO (THz UM-MIMO) systems was presented in [26]. The basic principles of beamforming via UM-MIMO were illustrated, alongside the analysis of the far-field and near-field assumptions in THz UM-MIMO. However, the channel model and measurement were limited to frequencies less than 1 THz. In high-mobility outdoor scenarios, the beam misalignment caused by Doppler expansion was not considered. A detailed review of interference management in 5G and beyond networks was carried out in [27]. The authors explained the interference types, and a thorough literature review in addition to technical discussion of suitable management schemes. The major interference challenges that are likely to be faced in future 6G networks were addressed, and as well as insights into the proposed new interference management methods, including indispensable guidelines for an AI-based solution. This review is expected to serve as a guide to the industry in determining the most appropriate technology for interference management. However, AI-based interference management using Deep Reinforcement Learning (DRL) was not explained.

In [28], a novel approach for femto-cell management for heterogeneous networks was introduced. Better performance in terms of delay, throughput, packet loss rate and energy consumption was achieved through the method. The approach cannot be applied in a region with other types of BS such as macro-cell, micro-cell and pico-cell networks. The Bayesian Inference for Interference Mitigation was adopted in [29]. This method can offer an efficient and dependable solution for optimizing overall performance in 5G cloud networks. The algorithm developed is not dynamic; it can only be used for another network with the same frequency band. The issue of interference and noise problems in 5G and Beyond Networks was reported in [30]. Emphasis was laid on the significance of strong interference management to maximize the performance of future wireless communication systems. The research employed the newest measurement-based channel models to reliably analyze interference statistics across a variety of deployment circumstances. In addition, the prospective solutions that enable full-duplex functioning in 5G systems by reducing the consequences of self-interference were examined, although, the authors did not address the issue of boosting the efficiency of spectrum utilization that can be attained through dynamic spectrum sharing techniques using full-duplex technology. A comparison table summarizing the conventional methods of interference mitigation, their performance and limitations is as shown in Table 2.

TABLE 2. A comparison table summarizing the conventional methods of interference mitigation, their performance and limitations.

Methods	Performance	Limitations
Power control technique	It is a standard industrial technique for interference mitigation [22] and preservation of service quality. Power control dynamically regulates the transmitter power output.	The technique often struggles with the dynamic, heterogeneous nature of 5G, particularly in mitigating CCI and CLI in ultra-dense networks (UDNs), and at times can lead to network instability.
Enhanced Inter-Cell Interference Coordination (eICIC)	eICIC schemes coordinate resource usage among cells to avoid signal overlaps in the frequency and time domains. This comprises the ideas of soft frequency reuse (SFR) and nearly empty sub-frames that have been applied to diverse 5G networks [31].	This technique fails to handle rapid channel changes as it struggles with high computational overhead, signaling latency, and limited effectiveness against dynamic TDD cross-link interference.
Beamforming	Particularly in large multiple-input multiple-output (MIMO) systems, beamforming spatially directs signal energy toward targeted users while reducing interference to others.	Despite the criticality for 5G network performance, these systems also face high Channel State Information (CSI) feedback overhead in FDD systems and require complex, precise calibration.
Resource Allocation (RA) Strategies	RA strategies such as dynamic frequency allocation, time-slot scheduling, and modulation adaptation seek to allocate limited spectrum resources.	RA strategies face the challenges of extreme density of devices, dynamic traffic demands, and the inherent complexity of ultra-dense heterogeneous networks (HetNets), and there is often increasing BER because of imperfect CSI.

4. DL-Based Channel Estimation and SIC for NOMA 5G system

An innovative method for mitigating interference in 5G networks, machine learning (ML) can greatly improve the dependability and quality of communication. It is anticipated that AI/ML will be essential to 5G networks [28]. In IoT networks, load balancing and interference reduction have made use of Deep Learning (DL). The DL method is more resilient than conventional methods since it uses fewer training pilots and does away with the cyclic prefix (CP). The goal is to lessen the effects of interference brought about by overlapping signals from various users, base stations, or radio access networks, which can degrade network performance, particularly in heavily populated or complicated environments.

In this section, the details of DL-Based Channel Estimation and SIC for NOMA-enabled 5G systems are presented. Since SIC is inherently sequential and structured, a Convolutional Neural Network (CNN) can be easily integrated into its loop. This novel approach is advantageous for handling non-linear interference, improving robustness to imperfect CSI, reducing error propagation, and facilitating hardware implementation. For simplicity, the architecture of CNN is presented in Figure 3.

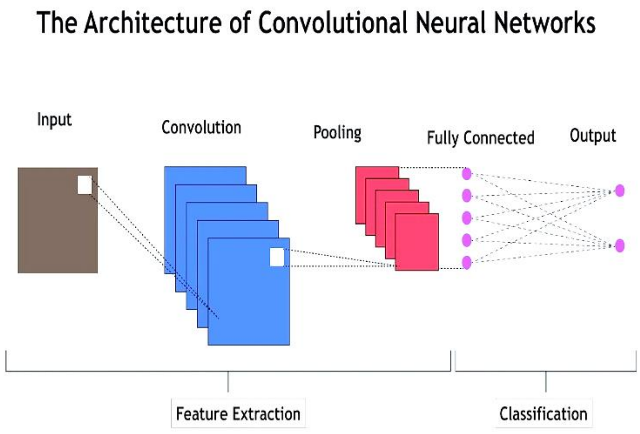


Fig. 3. The architecture of CNN.

The input layer comprises a set of data usually in matrix form which is channel state information (CSI). The local features are extracted by the convolution layer using filters (kernels). At this stage, learnable bias parameters can be added to improve model flexibility. Moreover, to improve convergence, activation function (ReLU) expressed as:
$\sigma(x) = \max(0, x)$ (ReLU i.e Rectified Linear Unit) is introduced, while in the pooling layer, the spatial dimensions are reduced to decrease the width and height of feature maps and preserve the most essential information. The smaller the feature map, the fewer the neurons in the later layers. In the fully connected layer, each neuron is connected to all outputs from previous layer. Then, the output of the CNN can be expressed as:

$$Y_{i,j}^{(k)} = \sum_{m=0}^{F-1} \sum_{n=0}^{F-1} \sum_{c=1}^{C} W_{m,n,c}^{(k)} X_{i+m,j+n,c} + b^{(k)} \quad (1)$$

where, $Y_{i,j}^{(k)}$ is the output value at spatial coordinates (i, j) in the k-th feature map of the output layer, $W^{(k)}$ is the learnable weight of the k-th filter at spatial position (m, n) and input channel c, F is the spatial size of the square convolutional filter/kernel, $b^{(k)}$ is a learnable scalar bias term specific to the k-th filter, and C is the number of channels in the input volume, and $X_{i+m,j+n,c}$ is the input value located at the shifted spatial coordinates (i + m, j + n) for input channel c.

4.1. CNN-Based Channel Estimation Model

The correct channel state information (CSI) provided by channel estimation is essential in wireless systems for beamforming, resource management, and coherent detection [32]. Traditional approaches such as Least Squares (LS) and Minimum Mean Square Error (MMSE) employ linear models and assume specific noise and channel distributions, which often lead to poor performance in real-world situations [33]. The advent of deep learning (DL), a subfield of machine learning (ML), has created significant opportunities in wireless communication. Models such as Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in modeling complex, high-dimensional, nonlinear interactions, as [34] demonstrated. Because they outperform conventional techniques in challenging propagation scenarios, their use in channel estimation is expanding rapidly. Channel estimation is treated as a nonlinear regression problem in CNN [35], which can be expressed as:

$$\widehat{H} = f_\theta(Z) \quad (2)$$

where, $\widehat{H}$ is the channel characteristic, f_θ is the CNN mapping, θ is the trainable parameter and Z is the input feature tensor. The estimated channel $\widehat{H}$ is obtained by passing the observed data Z through a learned model f_θ. In the case of multi-layer CNN mapping, the channel vector is given as:

$$\widehat{H} = f_\theta(Z) = f^{(L)}\left(f^{(L-1)}\left(\dots f^{(1)}(Z)\right)\right) \quad (3)$$

where, $f^{(1)}, f^{(2)}, \dots . f^{(L)}$ represent individual layers of the neural network. For the final output layer,

$$\widehat{H} = \widehat{H}_R + j\widehat{H}_I \quad (4)$$

where, $\widehat{H}_R, \widehat{H}_I$ are real and imaginary parts. So, instead of treating the channel as a simple real value, it is treated as a complex number, since the signals are sinusoidal waves having both magnitude and phase. Extending this model to time-varying channels to capture temporal dynamics, the time-series input is given by:

$$Z(t) = [Z(t), Z(t-1), \dots, Z(t-T)] \quad (5)$$

It can be deduced from (5) that, in wireless channels, signals are time-dependent, with current values depending on past values. The feature vector $Z(t)$ helps capture the interference pattern in the channel over time.

4.2. CNN-Based SIC Model

The interference effects of several signals are mitigated by the successive interference cancellation (SIC) method used in 5G networks, which leads to higher performance, particularly in situations where multiple users or devices transmit in the same spectrum. By enhancing the overall signal quality, data speeds, and spectrum efficiency, SIC is a crucial component of today's wireless communication networks, such as 5G [36]. Due to the high user density, spectrum sharing, and more complicated network settings (e.g., ultra-dense networks, device-to-device communication), SIC is essential in the context of 5G. Conventional SIC's central idea is to first decode the strongest signal (typically from the user with the best channel conditions), as Figure 4 depicts. Then, remove the decoded signal from the received signal, and then decode the next strongest signal, continuing in this manner until all signals are decoded and interference is minimized.

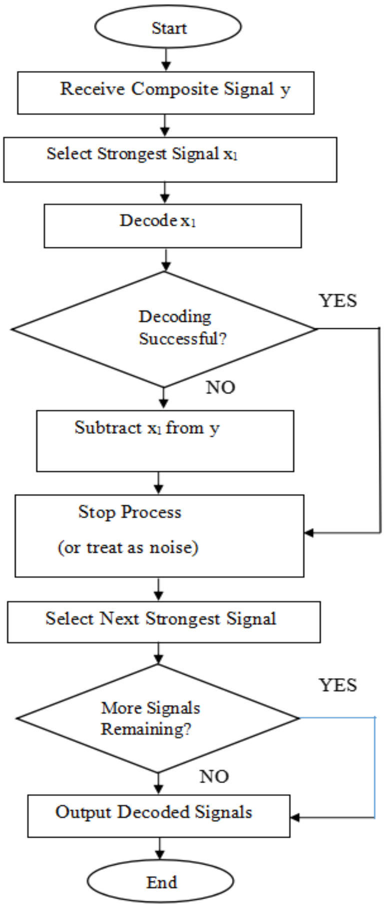
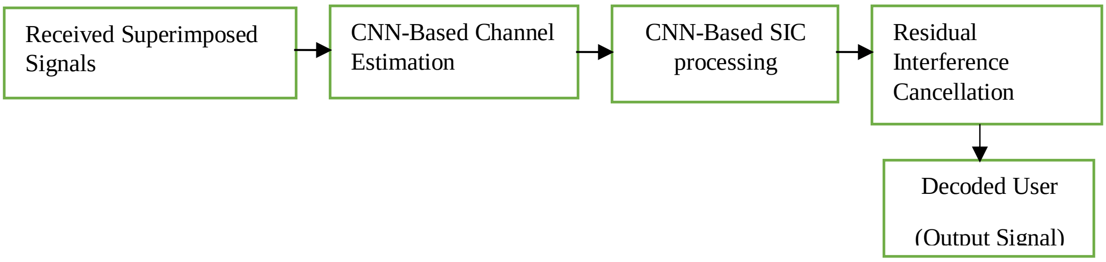


Fig. 4. Step-by-step outline of conventional successive interference cancellation technique.

DL/CNN-based SIC is a data-driven extension of conventional SIC in 5G NOMA systems [14]. While traditional SIC relies on analytical signal processing and accurate channel estimation to perform cancellation effectively, DL-based SIC learns the interference cancellation process from data, thereby enhancing robustness against channel uncertainty, reducing error propagation, and improving detection performance in complex wireless environments. Traditional SIC provides the fundamental principles, whereas DL-based SIC augments or replaces its model-based operations with learned representations. The block diagram of Figure 5 illustrates the summary of the DL-based SIC framework.



Mathematically, consider a downlink NOMA system with Kusers sharing the same resource block, the transmitted signal x is given as in (7):

$$x = \sum_{k=1}^{K} \sqrt{P_k}\, s_k \qquad (7)$$

where, $s_k \in \mathcal{S}$is the modulated symbol of the user k, $P_k$is the power allocation ($P_1 > P_2 > \cdots > P_K$). On the other hand, the received signal is given as:

$$y = \sum_{k=1}^{K} h_k \sqrt{P_k}\, s_k + n \tag{8}$$

where, $h_k$is the channel coefficient, and $n \sim \mathcal{CN}(0, \sigma^2)$ is the Additive White Gaussian Noise (AWGN). For Interference Learning, instead of explicit subtraction, CNN learns the datasets of the received signals as in (8), and the mapping process is given as:

$$f_\theta(y) \approx (s_1, s_2, \dots, s_K) \tag{9}$$

s_K is the probability that the input belongs to class k, while the implicit interference cancellation is attained. Due to imperfection of SIC, a residual interference I_{res} is left behind, which can be extracted from the residual signal r_k. Both r_k and I_{res} can be modeled respectively as follows:
After cancellation,

$$r_1 = y - \hat{y}_1 \tag{10}$$

Substituting $y\ as\ in$ (8):

$$r_1 = \sum\nolimits_{k=1}^{K} h_k \sqrt{P_k} x_k + n - \hat{h}_1 \sqrt{P_1} \hat{x}_1 \tag{11}$$

Separating the first user the residual interference becomes:

$$r_1 = \sum\nolimits_{k=2}^{K} h_k \sqrt{P_k} x_k + n + \sqrt{P_1}\left(h_1 x_1 - \hat{h}_1 \hat{x}_1\right) \tag{12}$$

The last term represents residual interference that degrades detection in SIC. It also affects network performance by reducing the signal-to-interference-plus-noise ratio (SINR). Introducing the pilot symbol as in pilot-assisted SIC, the residual interference can be easily estimated and cancelled.

To compare the performance of the DL-based SIC and the existing methods of interference cancellation, DL-based SIC is considered a novel approach to interference cancellation that improves the overall performance of 5G networks compared to existing methods. However, robust SIC is needed due to imperfect Channel State Information (CSI) and for future dense user deployments. The performance comparison between DL-based SIC and existing methods from different literatures [14], [30], [36], [37] is summarized in Table 3.

TABLE 3. Performance Comparison between the DL-based SIC and the existing methods.

Performance Metric	Conventional SIC	Improved SIC variants	Classical ML method	DL-based SIC
BER Performance	Moderate	Improved	Good	Best among them
Error Propagation	High	Moderate	Moderate	Low
Robustness to CSI Errors	Low	Moderate	Moderate	High
Scalability	Limited	Limited	Moderate	High
Spectral Efficiency	Moderate	Moderate	Limited	High
Real-Time Detection	Moderate	Moderate	Moderate	Fast after training
Adaptation to non-linear channels	Moderate	Moderate	Good	High
Complexity performance trade-off	Moderate	Moderate	Good	Excellent

5. Conclusion

In this review paper, we have discussed the main concept of CNN-based SIC approach to mitigate interference in 5G network with NOMA systems. We compared the proposed technique with the previous methods of interference cancellation, and we highlight the gaps in the previous research works such as error propagation due to the presence of residual interference, which can be estimated and cancelled by employing pilot-symbol. Finally, the challenges and the open research directions of CNN-based SIC method have been identified, including the need for robust SIC under imperfect Channel State Information (CSI), real-time channel adaptation, and handling dense user deployments efficiently.

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